TRANSPORTATION IN AN ERA OF DISRUPTION: HOW GENERATIONAL DIFFERENCES AND NEW TRANSPORTATION TECHNOLOGIES ARE INFLUENCING TRAVEL BEHAVIOR

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TRANSPORTATION IN AN ERA OF DISRUPTION: HOW GENERATIONAL DIFFERENCES AND NEW TRANSPORTATION TECHNOLOGIES ARE INFLUENCING TRAVEL BEHAVIOR

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To all those who feared they could not, but did it anyways.

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LIST OF SYMBOLS AND ABBREVIATIONS

AV	Autonomous vehicles
BO	Blinder-Oaxaca
CFA	Confirmatory factor analysis
CFI	Comparative fit index
CI	Conditional independence
ECVO	Expectations to change vehicle ownership
EFA	Exploratory factor analysis
IC	Information criteria
ICT	Information and communications technology
JLC	Joint latent class
LC	Latent class
RH	Ridehailing
RMSEA	Root mean square error of approximation
SAV	Shared autonomous vehicle
SED	Socio-economic and demographics
SP	Stated preference
TNC	Transportation network company
VA	Vehicle availability
VO	Vehicle ownership

SUMMARY

Over the past decade, the transportation and travel behavior domain has undergone noticeable changes. The emergence of gig and platform economies in conjunction with the rise in sharing economy consumption, largely driven by businesses such as Uber, Lyft, Zipcar or Airbnb, has revolutionized the daily life and mobility of many travelers. In addition, the Millennial generation of travelers has demonstrated different travel habits and patterns compared to previous generations, with many initial studies showing a decline in driver's licensing rate, car ownership, and further delay in later life stage events. Together, these two changing forces have also bolstered each other's impact, with the younger generation developing into stronger consumers of the sharing and platform economy, giving rise to the expectations that the future of travel might be different than what we see today. Such a prospect, therefore, necessitates a deeper study of these changing forces, including whether their impacts last into the future, and how they interact with different aspects of people's mobility.

The main objective of this dissertation, accordingly, is to investigate the impacts of these changing patterns on transportation-related attitudes and behaviors. More specifically, this dissertation first examines how the attitudes of Millennials – currently the largest demographic in the U.S. (72.1 million as of July 2019 based on reports from Pew Research Center (2020)) – differ from those of the previous generation, and applies the Blinder-Oaxaca decomposition method to identify the driving forces shaping these differences and how the influence of those forces is likely to change Millennials' attitudes over time. We observe that although the attitudinal differences between Millennials and

Gen Xers are fairly modest, Millennials' attitudes are closer to those of Generation X as they gain on a host of life-stage variables such as marital status, income, and education. For example, if Millennials were married, employed, and earning higher incomes at the same *rates* as Generation X (but retaining the same level of sensitivity to these factors), the generational gap in the *currently pro-urban* attitude would be reduced by 24%.

Subsequently, this work employs a latent class model with distal outcome to investigate the travel mode impacts of ridehailing services, how their impacts differ across latent demographic cohorts and, more specifically, how shared (pooled) rides and their adoption and usage patterns differ by the identified latent cohorts. Our analysis points to three latent classes of ridehailing modal impacts each with distinctly different patterns: transit and taxis showed sizable shares of usage decline among the younger, lower-income, and urbanite ridehailers. On the other hand, higher-income and older ridehailers tend to belong to classes where ridehailing is largely supplemental to their use of other modes, but when there *is* an impact, it tends to be a reduction in the usage of personal cars and taxi cabs. Analyzing the association between these latent classes and shared ridehailing adoption and usage, we find our younger class to have the highest adoption rate and usage frequency of shared ridehailing. Moreover, we conclude that 30% of the total shared ridehailing adopters in our sample, and 50% of the frequent users (weekly users), are associated with the class of ridehailing modal impacts where transit and taxi are impacted the most.

This dissertation further investigates another important aspect of ridehailing services: their interaction with current vehicle ownership decisions and future intentions to change this important household commodity. Acknowledging that such a relationship is subject to heterogeneity in the population with respect to factors such as age and attitude, we use a joint (trivariate) latent-class modeling framework and present a detailed picture of how the factors influencing these decisions and their interactions vary across different latent population cohorts. More specifically, we see a less straightforward relationship between age and ridehailing usage frequency, for which other studies have generally pointed to a negative relationship. Our results reveal two latent clusters of approximately similar average age who show drastically different ridehailing usage frequency. Furthermore, although we see evidence of a negative association between vehicle availability and RH usage frequency, our latent class framework reveals two clusters with approximately similar vehicle availability but different ridehailing usage, pointing to the influence of other factors such as attitudes and the built environment in differentiating their ridehailing usage. With respect to the relationship between ridehailing usage and expectations to change vehicle ownership, our results show that, of the two clusters with similar vehicle availability and age, the one with higher ridehailing usage is less likely to expect an increase in household vehicle ownership within the next three years. This result shows some promise for the future impact of ridehailing services in containing increases in car ownership.

This dissertation, therefore, makes valuable contributions to the literature not only by furthering the knowledge on the concurrent roles of generational cohorts and emerging transportation technologies in shaping the future of travel, but also by helping introduce new methodologies to the field of travel behavior research. Ultimately, the empirical outcomes of this dissertation can help inform travel demand models, public transit agencies, private ridehailing companies, and transportation equity causes, while the new methodologies can help bring new insights in other areas of transportation research.

CHAPTER 1. INTRODUCTION

1.1 Background and Motivation

Scientific models have constituted the backbone of most scientific domains, enabling researchers, practitioners and policy makers to understand and predict various trends and phenomena. In the transportation field, travel demand and behavioral models are similarly used to understand people's choices and behaviors, and predict them in a larger context to model the flow of people and goods. However, in an era defined largely by fast-paced technological changes, apparent generational disparities, and sudden unexpected disruptions such as global pandemics, these models face the critical and challenging task of providing insights while tuned to hypotheses based on the old status-quo. How well these models can adjust to the changing realities is highly dependent on researchers correctly identifying the patterns of change and incorporating them in the modeling framework.

This dissertation is largely motivated by the changing landscape of the transportation domain over the past decade, where generational differences in attitudes and choices, the introduction of the gig economy in the form of app-based transportation services, the progress toward autonomous driving, and to cap off the decade, a global pandemic crippling most nations in the world, have disrupted the established norms of the behavioral and demand modeling in the field. This work aims to provide a better understanding of the first two of these changing forces, and ultimately help better equip travel demand models in their short- and long-term forecasts. Due to the unavailability of data, however, this dissertation does not empirically investigate the mobility impact of the last changing force, i.e. the COVID-19 pandemic, but discusses its implications for travel behavior in the Conclusions chapter.

Among the aforementioned forces of change, the generational trends and divides in transportation choices and attitudes pose a critical question to travel demand models, especially regarding their long-term forecasts. Much research over the past few decades has focused on analyzing transportation-related attitudes and behavior, but it has only been over the past several years that researchers have more specifically focused on the generational trends and divides in transportation choices and attitudes. Such a trend in research has been for a good reason, since the Millennials, those traditionally defined as born after 1981 and also known as Generation Y, have been exhibiting new trends in lifestyle and travel choices that have often defied the normal expectations and forecasts of planners, engineers, and policy makers. In the transportation field, the literature has cited a lower licensure rate, lower car ownership, higher interest in living in urban areas, and a more environmentally-aware lifestyle as some of the trend-bucking characteristics of the younger generation (Blumenberg et al., 2012; Delbosc et al., 2018; Garikapati, Pendyala, Morris, Mokhtarian, & McDonald, 2016; McDonald, 2015), therefore demanding a better understanding of the driving forces behind such changes in characteristics and their longevity.

The current literature on generational studies in transportation, or more specifically the literature on Millennials, has extensively studied how Millennials' *choices* and *behaviors* differ from the patterns of older generations. This literature, however, lacks studies on how Millennials differ in their transportation-related *attitudes*, despite substantial evidence for the strong role of attitudes in influencing behavioral choices in transportation. This gap in research on attitudinal differences is perhaps largely due to a lack of attitudinal data, requiring the majority of comparative studies on generational differences to rely primarily on behavioral indicators. Therefore, a driving force behind this dissertation, and more specifically the study in Chapter 2, is the belief that continued examination of attitudinal differences between Millennials and Gen Xers is critical to placing into context behavioral differences, with particular importance in the transportation sector where infrastructure planning revolves around forecasting travel behaviors, for which attitudes play an important explanatory role.

This generational disruption has become especially more prominent in the presence of the new technologies that have recently revolutionized the transportation field. Over the past several years, the concept of the sharing and platform economy, propelled by recent leaps in information and communications technology (ICT), has gained a strong foothold in the global market and has grown significantly in popularity. The appeal of such business models has also impacted the transportation sector, with companies such as Uber, Lyft, and Zipcar having changed the usual balance in the field. Among the multifarious impacts of such mobility services, the literature points to potentially lower car ownership levels, impacts on transit ridership, and also potentially higher congestion levels in urban areas (Circella & Alemi, 2018; Erhardt et al., 2019). These services, however, enjoy differing popularity levels among different segments of the population, with the younger generation believed to have adopted these new technologies faster and at higher rates, in addition to being expected to integrate them more tightly into their lifestyle. This difference in adoption rate and usage frequency has potential consequences for shaping different travel habits and influencing travel-related choices in the present and the future, further complicating current travel demand models' assumptions and predictions. Accordingly, another research thrust of this dissertation, more specifically covered in Chapter 3, is investigating how shared mobility services impact travel choices differently across the age spectrum and other sociodemographic characteristics, thus providing a more detailed map of shared mobility interactions with traditional travel modes and other travel choices.

A third topic of interest, with special implication for short- and long-term travel demand modeling forecasts, is the interaction of shared mobility services with vehicle ownership (VO) decisions. One of the initial promises of shared mobility services has been a reduced reliance on personal cars through providing on-demand car access. Such potential for change in vehicle ownership can have wide ranging implications not only for the automotive industry through changes in vehicle sales, but also for transportation and urban planning through requiring a different public space design such as, among other things, different curbside planning and parking space allotments.

While some studies have enforced such initial claims that ridehailing services can decrease vehicle ownership rates among households (Hampshire, Simek, Fabusuyi, Di, & Chen, 2017; Sabouri, Brewer, & Ewing, 2020; Ward, Michalek, Azevedo, Samaras, & Ferreira, 2019), others have cautioned and pointed out the opposite (Gong, Greenwood, & Song, 2017; Ward et al., 2021). Most such studies, in addition, only consider one direction of impact between these two variables, assuming that ridehailing usage impacts vehicle ownership or vice versa. It is, however, conceivable that there is a bidirectional relationship between these two variables; in other words, while for some individuals a low level of vehicle ownership may prompt a higher usage of ridehailing, for some others having access to ridehailing services may allow them to live with fewer vehicles. Considering the joint nature of these decisions, however, it is important to model these two variables together so as to take into account the shared unobserved variability between them. The third study of this dissertation, consequently, examines the interaction of ridehailing usage frequency, vehicle availability, and future intentions to change vehicle ownership, aiming to investigate how different classes of travelers vary in their (joint) decisions of using shared mobility and (current and future) vehicle ownership decisions, in addition to how the factors influencing these decisions differ among them. We should note that, ultimately, this study does not resolve the question of the most appropriate direction(s) of causality between ridehailing usage and vehicle ownership, but by modeling them both as *outcomes* in a joint model system (rather than one as cause and the other as outcome), we can better reflect their association and take advantage of the information provided by unobserved influences that are common to both outcomes.

Overall, a better understanding of the generational differences in travel-related attitudes and choices, in conjunction with differing tendencies toward the use of emerging technologies, is critical not only for a better understanding of the current and future needs of society, but also for maintaining and updating travel demand models (TDMs). Travel demand models are under a stronger focus now to test scenarios and provide results that account for the changing transportation landscape. The outcomes of this dissertation, therefore, may be used to inform travel demand models to better capture the evolving heterogeneity in the population within their scope.

1.2 Research Objectives

The overarching objective of this dissertation is to investigate the impacts of generational differences and new technologies on transportation choices and attitudes, and how likely it is for these impacts to last into the future. In the second chapter of this dissertation, accordingly, I focus on attitudes (as opposed to behaviors), and investigate generational differences in transportation-related attitudes. In doing so, this study aims to answer the following questions:

1. Is there a statistically and practically significant gap between Millennials and Generation X in their transportation-related attitude?
2. What are the most salient factors contributing to the attitudinal gap between the two generations? And,
3. How likely is it for these gaps to disappear as Millennials grow older and enter later life-stages?

The third chapter of this dissertation, subsequently, turns its focus to analyzing behaviors, and investigates the disparate modal impacts of ridehailing usage among latent population groups and how such impact patterns relate to the use of shared ridehailing. The main goals of this study include:

1. Identifying how the modal impacts of ridehailing differ by sociodemographic characteristics, including age, and,
2. Investigating the association between shared ridehailing usage and the identified modal impacts, and providing an assessment of the sustainability promise of shared ridehailing services based on such an association.

Finally, the fourth chapter in this dissertation, also focusing on ridehailing impacts, aims to analyze the joint relationship among ridehailing usage, household vehicle availability, and future intentions to change household's vehicle ownership. The goals of this chapter include:

1. Investigating the joint relationship between ridehailing usage and vehicle availability without assuming a one-directional relationship between them,
2. Incorporating generational and lifestyle heterogeneity by including age and attitudes into the joint analysis so as to more accurately capture the nuances of the joint relationships, and
3. Investigating how *current* ridehailing usage and vehicle ownership decisions are related to *future* intentions to change household's vehicle ownership.

1.3 Dissertation Structure

This dissertation consists of three studies, each one employing a different statistical method to analyze the influence of generational differences or emerging technologies on travel attitudes and behaviors. Each study is presented as a standalone journal article, starting with an abstract and introduction and culminating in a summary and conclusion. Table 1 provides a summary of the key characteristics of each study.

Chapter 2, as mentioned, focuses on four transportation-related attitudes, and applies the *Blinder-Oaxaca decomposition* method to examine the existing generational gaps and how they might evolve over time. We present a summary of the literature in the area and move on to introduce the dataset in our analysis. We subsequently discuss the derivation of the attitudinal constructs and analyze the generational gap for each attitude. Afterwards, we apply the Blinder-Oaxaca decomposition method to the identified gaps and discuss the results for each attitude. We conclude the paper with a summary of the findings.

Chapter 3 first uses a *latent-class clustering (profiling) approach* to uncover the heterogeneous influence of ridehailing services on the use of traditional travel modes. Building on that analysis, a *latent class model with distal outcome framework* is used to investigate how the adoption and usage of shared ridehailing is differently associated with each latent profile. The paper similarly starts with a discussion of the literature on the topic, and after describing the dataset for our analysis, presents the first part of our methodology and discusses the results of the exploration of the heterogeneity of the modal impacts of ridehailing. The second portion of the paper, then, describes the latent class with distal outcome framework, how it is implemented in our context, and its results. We conclude the paper with further discussion and summary of the findings.

Chapter 4 employs a *joint latent class modeling framework* to simultaneously classify and model the ridehailing usage frequency, vehicle availability, and future intentions to change vehicle ownership levels and their relationships. This study first presents a gist of the literature on each of the three topics involved and discusses how the current paper contributes to the literature. The dataset is then introduced, after which we discuss the proposed methodology and its distinctive features. The results are then presented, followed by a discussion and summary of findings.

Table 1 Summary of the research studies of this dissertation

Study 1: Investigating generational differences in transportation-related attitudes	
Research questions:	Do Millennials differ in key travel-related attitudes from Gen Xers? What factors contribute to the existing generational gap? How likely is it for the attitudinal gap to close as Millennials age?
Dataset:	2015 California Millennials dataset
Methodologies:	Confirmatory factor analysis, Linear regression model, Blinder-Oaxaca decomposition
Study 2: Investigating the modal impacts of ridehailing services: is shared ridehailing the answer?	
Research questions:	How do ridehailing services impact the use of other modes across different segments of the population? How are shared ridehailing adoption and its determinants associated with the different profiles of ridehailing modal impacts?
Dataset:	2018 California mobility dataset
Methodology:	Latent class model with distal outcome
Study 3: Joint latent class analysis of shared mobility adoption and vehicle ownership level	
Research question	How do differing segments of the population vary in the adoption of shared mobility and vehicle ownership?
Dataset	2018 California mobility dataset
Methodology	Joint (trivariate) latent class model

1.4 Major Contributions

This dissertation contributes to the literature, first, by introducing new methodologies to the field that have previously not, or have only rarely, been used in the travel behavior domain, and second, by applying them to timely topics in the field and providing novel insights. To our knowledge, the first study in this dissertation is the first exploration of generational differences in transportation-related attitudes, with the application of the Blinder-Oaxaca decomposition method among the first in the travel behavior field. The results of this study are also of particular impact, showing that life-stage-related (endowment) disparities, such as in employment status, student status, income level, and marital status, explain significant portions of the overall attitudinal gaps. Furthermore, we were able to evaluate what percentage of the existing gap may reasonably be expected to disappear as the Millennials get older. For example, if Millennials were married, employed, and earning higher incomes at the same *rates* as Generation X (but retaining their own model *coefficients*), the generational gap in the currently pro-urban attitude would be reduced by 24%. On the other hand, we may expect little change in Millennials' pro-environment attitude as their life-stage-related (endowments) characteristics become more similar to those of Gen Xers' (assuming, again, they retain their own model *coefficients*, or sensitivities). Such results further help put into context the hype around Millennials, and whether planners and engineers need to consider such differences as they plan for the future of transportation.

Furthermore, exploring the modal impacts of ridehailing services, in general, and shared ridehailing services, more specifically, in addition to how these modal impacts differ by sociodemographics, help better paint a picture of transportation network companies' (TNCs') impacts on society. This topic is of even greater interest considering that shared ridehailing services are often proposed as a sustainable solution, and therefore an empirical analysis of their modal impacts, so far rather scarce in the literature, can add valuable insights into the role of these services in sustainability. Our results show how the younger lower income cluster, in contrast to the older higher income clusters, tends to replace transit trips with ridehailing ones, a result with important implications for public transit agencies. This work further shows how a significant portion of the frequent shared ridehailers is associated with the younger, lower income cluster where ridehailing specifically impacts transit, therefore adding concerns regarding the sustainability promise of shared ride services. In addition, the methodology used in this analysis, i.e. latent class with distal outcome model, has rarely been used in travel behavior research before, and considering its potential applications can be of great interest to the travel behavior field.

Lastly, the third study uses a unique methodology to jointly model current vehicle availability and future vehicle ownership intentions alongside ridehailing usage. The joint latent class model used in this study, to the best of our knowledge, is the first application of this model in the travel behavior field and can be of particular interest to the research community in studying joint phenomena while explicitly accounting for latent heterogeneity. Furthermore, the outcome of this study is of particular significance to the travel behavior field and auto industry, with the results further illuminating how different population subgroups vary with respect to their use of ridehailing services and current and future vehicle ownership decisions. For instance, we discuss how, as opposed to what most studies in the literature show, the younger generation should not necessarily be associated with a higher use of ridehailing, and how incorporating attitudes helps account for the heterogeneity among the younger generation.

This dissertation, therefore, helps bring more diverse and sophisticated methodologies to the field, and the results of the work presented here can inform travel demand models in better working with future scenarios and provide more accurate results.

CHAPTER 2. INVESTIGATING THE GENERATIONAL DIFFERENCES IN TRANSPORTATION-RELATED ATTITUDES

2.1 Abstract

Considerable recent work suggests that Millennials' behaviors may be converging with those of Generation X as they enter later life stages, but few have investigated whether attitudes, which are often strong predictors of behavior, are undergoing the same convergence. In this study, we analyze the existing generational gap in four transportation-related attitudes (*currently* pro-urban, *long-term* pro-urban, pro-car ownership, and pro-environment), and examine the differential effects of other characteristics, including life-stage variables, on these attitudinal gaps. We apply the threefold Blinder-Oaxaca decomposition method to a statewide (weighted) sample of 1029 Millennials and 946 Generation Xers from California to unravel these effects. The method distinguishes among: (1) effects due to the cohorts having different *characteristics* (*endowments*); (2) effects due to those characteristics having different *influences* on attitudes (*coefficients*); and (3) the *interaction* of those two effects. We observe that Millennials' attitudes: (1) differ from those of Generation X only by small, albeit statistically significant, amounts on average; and (2) *are* closer to those of Generation X as they gain on a host of life-stage variables such as marital status, income, and education. For example, if Millennials were married, employed, and earning higher incomes at the same *rates* as Generation X (but retaining their own model *coefficients*), the generational gap in the currently pro-urban attitude

would be reduced by 24%. This study brings an econometric approach to the study of generational divides in transportation-related attitudes, with findings suggesting that Millennials might be leaving part of their uniqueness behind as they enter later life stages.

2.2 Introduction

Although in modern times all generations have engendered a certain amount of media attention, the Millennials cohort has disproportionately enjoyed a spotlight so intense that, for many, the word “Millennials” now evokes something of an ad nauseum catchphrase. Examining the deluge of popular news, opinion, and academic pieces on Millennials makes it clear that this fascination can be traced to several attributes, the most notable of which is that (based on national and global projections) Millennials will soon become the largest living adult cohort (having been the largest living cohort among all age groups since the 1990s), a prediction with reverberating implications across all domains. Compounding this demographic dominance is the fact that members of this cohort have long been making choices that fly in the face of trends observed in prior generations, although several studies have suggested that some of these contrasting behaviors may be converging with those of prior generations as Millennials enter later life stages. Identified behavioral differences between Millennials (defined here as those born in the 1980s and 1990s; also known as Generation/Gen Y) and the preceding Generation X (born between 1965 and 1980; also referred to as Gen X) have been attributed to a range of personal (ex. attitudinal differences, technological exposure), environmental (ex. built environment policies intended to encourage denser living), and economic (ex. effects of recession) factors (Blumenberg et al., 2012; Delbosc et al., 2018; Kuhnimhof et al., 2012; Thigpen & Handy, 2018).

Within transportation, there is substantial evidence that attitudes play a role in influencing behavioral choices (Domarchi, Tudela, & González, 2008; Kitamura, Mokhtarian, & Laidet, 1997; Kuppam, Pendyala, & Rahman, 1999; Mokhtarian & Salomon, 1997). However, due largely to a lack of attitudinal data, the majority of comparative studies on generational differences have relied primarily on behavioral indicators, although there are segments of the literature that have examined market-oriented attitudes such as brand loyalty, or work/life-oriented attitudes such as satisfaction. We assert that continued examination of attitudinal differences between Millennials and Gen Xers is critical to placing into context behavioral differences, with particular importance in the transport sector where infrastructure planning revolves around forecasting travel behaviors, of which attitudes play an important explanatory role. To our knowledge, this study is the first, in the dense collection of Millennials literature, to apply a decomposition approach, specifically the Blinder-Oaxaca (BO) method, to extricate group (endowment) and effect (coefficient) differences influencing transport-related attitudinal gaps between Millennials and Gen Xers. As such, while this study contributes specifically to the Millennials literature, it may also inform future work on other generational and demographic divides of interest within transport contexts.

The remainder of this chapter is organized as follows: We first provide an overview of the literature on attitudinal and behavioral differences between Millennials and prior generations, followed by an introduction of the dataset. Next, we detail the attitudinal statements and resultant constructs examined in this chapter, after which we analyze statistical differences between generations for the selected transport-related attitudinal constructs. We then introduce and apply the Blinder-Oaxaca method to decompose significant gaps in attitudinal constructs between generations, and close with limitations and avenues of future exploration for this work. We consign to an appendix the multiple underlying regression models on which the BO analysis is based, as well as the interpretations of those models, so that the main body of the chapter can concentrate attention on the distinctive features of this study. The appendix also contains additional, higher-level analysis of the BO decompositions.

2.3 Background

Millennials have been studied extensively in the business and marketing domains, motivated by expectations that this generation will be a lucrative consumer segment for a plethora of industries. The travel and hospitality industries have most conspicuously taken note of these changing times, fueled by characterizations that Millennials prefer to spend their money on experiences (as opposed to products), as well as findings that Millennials are more likely to report desires to travel abroad (Barton et al., 2013; Benckendorff, 2010; Bilgihan, 2016; Rita et al., 2018). As such, associated entities, such as the hotel and airline sectors, have set about studying traits such as brand loyalty, digital shopping attitudes and behaviors, and social media influences on Millennials' choices (Barton et al., 2013; Benckendorff, 2010; Bilgihan, 2016). From a more general commerce perspective, it has been established that Millennials are devoted consumerists, with these traits reflected in increased tendencies to spend money easily and to view shopping as leisure (Belleau et al., 2007; Benckendorff, 2010; Niehm & Ma, 2006). Interestingly, nonprofits and philanthropic groups have also recognized the importance of capturing Millennials as donors, with studies showing that Millennials have positive attitudes toward charitable organizations (Gorczyca & Hartman, 2017) and suggesting that technology-based solicitation, crowdfunding, and social alliances are useful tools to capture the support of this generational segment (Gorczyca & Hartman, 2017; Paulin et al., 2014). Due to the apparent altruism of this generation, for-profit businesses are finding that they too can attract Millennial consumers with cause-related marketing (Liu & Ko, 2011; Marlen et al., 2009).

The next most developed mass of literature on Millennials comes from the workplace domain, as employers and organizations prepare for a generation that already comprises a plurality of the U.S. workforce (Fry, 2018; Jerome et al., 2014). Researchers find that while Millennials seek skill development and advancement (Ng, Schweitzer, & Lyons, 2010), they place emphasis on achieving work-life balance in the form of a satisfying life outside of work (Ng et al., 2010; Straub, Zhang, & Kusyk, 2007). It has also been found that in some regards, Millennials place higher value on purpose over salary, and may be more attracted to businesses that display corporate social responsibility (McGlone et al., 2011). Work by Weber (2017) shows that from a leadership perspective, Millennials are more self-focused (as opposed to others-focused) compared to managers from the 1980s and 2010s.

Regarding transport and land use, Millennials have been capturing the attention of transportation professionals ever since they came of age, with increased preferences for living in urban centers (Delbosc & Nakanishi, 2017; Okulicz-Kozaryn & Valente, 2018), accompanied by reduced rates of licensure (Delbosc & Currie, 2013; Sivak & Schoettle, 2011, 2012), vehicle ownership, and vehicle miles traveled (VMT) (Hopkins, 2016; Kuhnimhof et al., 2012; Polzin, Chu, & Godfrey, 2014), leading to them being dubbed the "go-nowhere" generation (Buchholz & Buchholz, 2012; McDonald, 2015) (in contradiction to their afore-discussed penchant for traveling abroad). Recent work has suggested that differences in transport choices may be attributable to temporary environmental/external factors; for example, as Millennials enter later life stages (i.e., with children/families), lack of affordable options such as urban housing (among other reasons) may be causing their behavioral patterns to converge with those of prior generations (Delbosc & Nakanishi, 2017; Garikapati et al., 2016; Lavieri et al., 2017). Relatedly, researchers have found that some behavioral differences may be due to economic factors, suggesting that as Millennials become more financially independent, attributes like vehicle ownership may converge with or even surpass those of prior generations (Klein & Smart, 2017; Lavieri et al., 2017). External factors of influence that are less likely to change over time include recent policies intended to encourage smart development (ex. denser living), as well as increased alternatives/incentives for more sustainable modes (Delbosc & Currie, 2013; Thigpen & Handy, 2018). While it is critical to keep these external agents of influence in mind, several studies find that attitudes and/or cohort effects also contribute to differences such as the licensing decline (Delbosc & Currie, 2013; Thigpen & Handy, 2018), increased public transit usage (Hopkins, 2016; Newbold & Scott, 2018), and multimodality among Millennials (Circella et al., 2017a, Lee et al., 2018). As mentioned, this chapter seeks to extend the understanding of differences in transport-related attitudes between Millennials and Gen Xers.

Thus, we see that many of the attitudinal and behavioral studies of Millennials are motivated by the goal of understanding this generation as a core market segment, with the intent of capturing their loyalty (and dollars) as consumers. Furthermore, Millennials are seen as a growing component of the labor force, and organizations are striving to attract and retain a generation who are purported to have differing work/life attitudes and behaviors compared to the workers before them. With similar motivations from the transport perspective, understanding generational divides is critical for engineers and planners as we work toward forecasting, planning, and designing infrastructure systems that must serve a multi-generational society, a large portion of whom are and will be from the Millennial cohort for several decades to come.

2.4 Overview of dataset

Data used in the analysis for this chapter comes from the first wave (2015) of survey data obtained in a multi-year research effort designed to investigate emerging transportation trends in California with a focus on Millennials and Generation X. The study used a quota sampling approach on an online opinion panel. Approximately 2400 total respondents (N = 1975 after excluding ineligible, inattentive, or incomplete cases; only members of the Millennial and Gen X cohorts were retained) were recruited across age groups, as well as across combinations of six geographic regions and three neighborhood types in California. The sampling process used targets for gender, age, race and ethnicity, household income, and presence of children in the household to capture as much of the population's diversity as possible. Further, to partially correct for sampling and nonresponse biases, the dataset was weighted to reflect the population distributions on several sociodemographic traits for Millennials and Gen Xers residing in California. Table 1 provides an overview of the descriptive statistics for the sample. Additional details regarding study implementation, survey variables, and sociodemographic distributions are presented in Circella et al. (2016, 2017b).

Table 2 Selected sociodemographic characteristics of the sample (N = 1975)

Variables	Characteristics	Frequency[a]							
		Unweighted				Weighted			
		Gen Y		Gen X		Gen Y		Gen X	
		N	%	N	%	N	%	N	%
Gender	Female	629	58.3	525	58.6	518	50.4	481	50.8
Race	White	405	37.5	600	33.0	527	51.2	525	44.5
	Asian	188	17.4	136	15.2	177	17.2	175	18.6
	Hispanic	271	25.1	150	16.7	445	43.2	266	28.1
	African-American	50	4.6	47	5.2	36	3.5	43	4.5
	Native American	39	3.6	28	3.1	40	3.8	25	2.6
Age[b]	18-24 years	335	31.0	-	-	400	38.9	-	-
	25-34 years	744	69.1	-	-	679	61.2	-	-
	35-44 years	-	-	584	65.2	-	-	629	66.5
	45-51 years	-	-	312	34.8	-	-	317	33.5
Annual household income	<US $40K	351	32.5	207	23.1	329	33.0	183	19.4
	US $40K-$100K	472	43.8	414	46.2	385	37.3	342	36.2
	> US $100K	176	16.3	220	24.6	237	23.0	366	38.7
Education	High school diploma or less	193	17.9	102	11.4	184	17.8	81	8.5
	Some college or technical school	452	41.9	341	38.1	425	41.2	329	34.8
	College degree	332	30.8	306	34.2	308	29.9	345	36.5
	Graduate degree and higher	98	9.1	143	16.0	107	10.3	189	20.0
Employment	Employed	689	63.9	612	68.3	796	77.4	796	84.2
Occupation	Full-time student	166	15.4	24	2.7	178	17.3	30	3.2
	Manager	97	9.0	129	14.4	121	11.7	183	19.4

Table 2 Cont'd

	Professional/ technical	148	13.7	193	21.5	174	16.9	259	27.4
	Clerical/ administrative	106	9.8	78	8.7	109	10.0	87	9.2
	Other[c]	338	49.0	212	23.7	392	49.2	267	28.2
HH size	Single-person HH	170	15.8	131	14.6	158	15.4	120	12.7
	Two-person HH	267	24.7	203	22.7	244	23.7	212	22.4
	Three-person HH	248	23.0	211	23.5	243	23.6	227	24.0
	Four-person or larger HH	394	36.5	351	39.2	384	37.4	387	40.9
Marital status	Married	412	38.2	557	62.2	370	36.0	606	64.1
Built environment	Urban dweller	209	19.3	173	19.3	289	28.1	240	25.4
Political affiliation	Republican	183	17.0	196	21.9	153	14.8	180	19.0
	Democrat	433	40.1	322	35.9	428	41.6	370	39.1

[a] Frequencies do not add up to 100% or the total N because of rounding errors, non-responses, or "other" categories.
[b] Average age (weighted sample): 33.8 years (median: 33.0 years); lowest age: 18 years; highest age: 51 years.
[c] Includes education/training, service and repair, sales or marketing, production or construction, and other.

2.5 Attitudinal constructs

The survey used in this study measured individual attitudes through 66 variables that collected information on a variety of topics including adoption of technology, residential preferences, vehicle ownership, travel behavior, etc. using a 5-point Likert-type scale ranging from "Strongly disagree" to "Strongly agree". Exploratory factor analysis (specifically, principal axis factoring with maximum likelihood estimation and oblique rotation) was first executed across the full set of statements (Circella et al., 2017b), after which confirmatory factor analysis (CFA) was applied across 14 of the initial 66 statements to extract four transportation-related constructs for further study. The selected attitudinal constructs represent desires for an *urban lifestyle*, separately in both present and future time frames, *feelings toward owning a private vehicle*, and *attitudes toward environmentally conscious living*. These constructs are selected due to their conceptual and/or empirical relationships with transport-related behaviors, and because they are also stereotypically expected to differ between Millennials and older cohorts (Delbosc & Nakanishi, 2017; Forward et al., 2010; Hopkins, 2016; Malokin et al., 2017; Shaw et al., 2018).

A visual representation of the constructs is shown in Figure 1, which follows latent variable diagram convention with single-headed arrows representing the effects of constructs on observed indicators, and double-headed arrows representing correlations between variables (Loehlin, 2004). Significant correlations between constructs are retained; item error correlations were also tested for significance, but most were ultimately restricted to zero (consistent with the assumption that the latent variable accounts for most of the correlation between items), with the exception of one significant error correlation shown in the diagram which both increases the fit of the model and is conceptually interpretable (i.e. having shared sources of unexplained variation between the respective statements is logical). The overall CFA model has acceptable fit with an RMSEA of 0.061 and a CFI of 0.902. The chi-squared test of discrepancy between the sample and model-implied covariance matrices is significant ($\chi^2 = 578.667$, df = 70, $p < 0.001$, $\alpha = 0.05$), but this may be attributable to the large sample size and is therefore a minor concern. Factor scores (continuous variables indicating respondents' relative measurements on each latent construct or factor) for the derived attitudinal constructs are computed using linear regression with the mean vector and covariance matrices from the fitted model (StataCorp, 2017), and standardized across the sample.

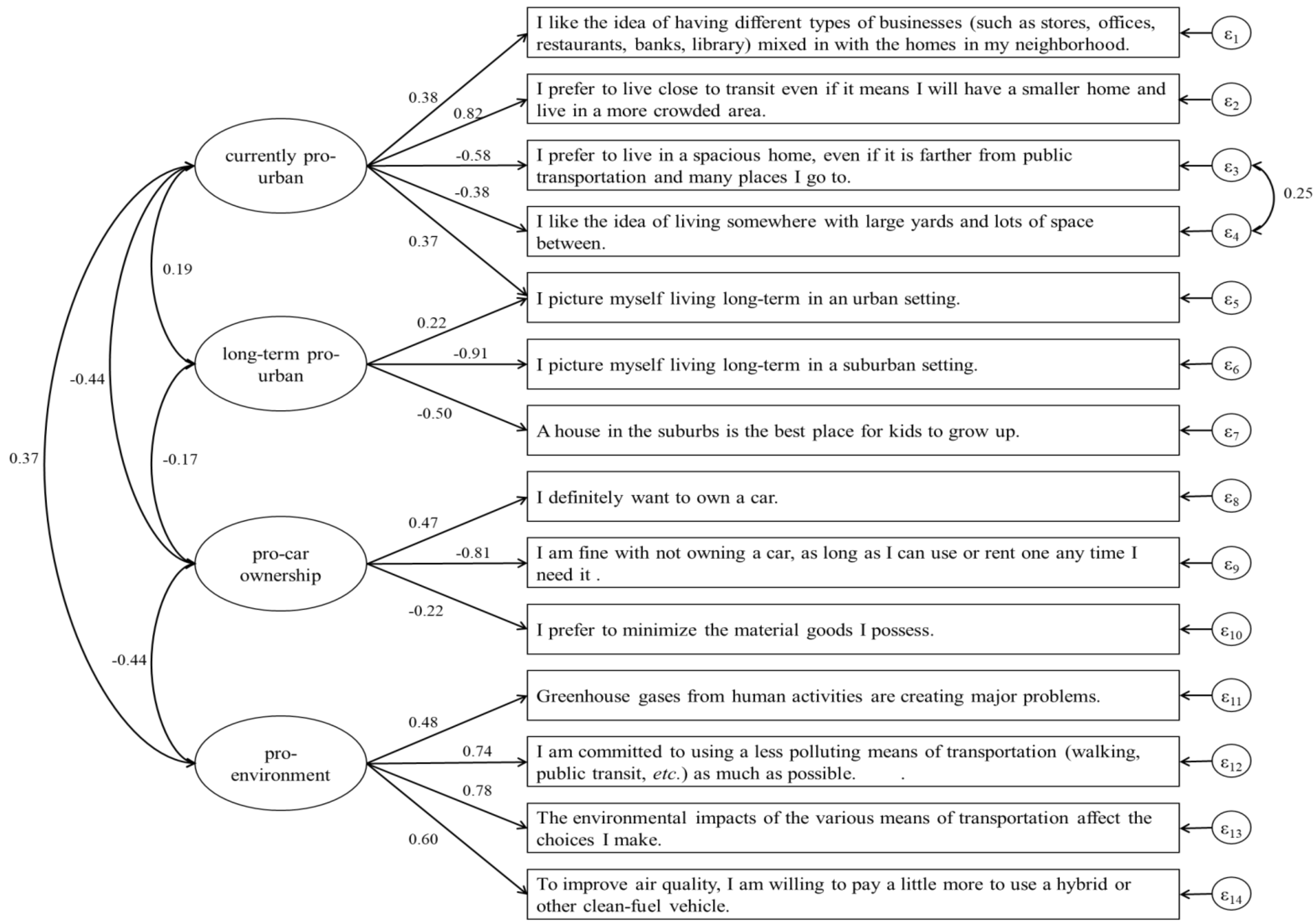


Figure 1 Confirmatory factor analysis of transportation-related attitudinal constructs (N = 1975)

2.5.1 Currently pro-urban

Numerous findings concur that Millennials have increased tendencies to prefer urban environments with denser land use (Delbosc & Nakanishi, 2017; Okulicz-Kozaryn & Valente, 2018), while their parents (i.e. Generation X) epitomize the suburban lifestyle, with their minivans and long commutes. This construct allows us to test that expectation with the current sample, as it reflects the mindset of respondents toward living in urban rather than suburban or rural areas – residential location choices that are critically tied to travel behavior (Ewing & Cervero, 2010; Handy, Cao, & Mokhtarian, 2005; Lavieri et al., 2017). A higher score on this construct tends to signify a preference for living in mixed-use developments with high transit accessibility, even if it means sacrificing larger home and/or yard sizes. As alluded to earlier, the statements measuring attitudes toward large homes and yards were allowed to have correlated error terms, since it is conceptually plausible that common unobserved variables help explain the variance in both of these items. The inclusion of the error term correlation produces an increase in fit for the overall model.

2.5.2 Long-term pro-urban (i.e., long-term urbanite)

While the prior construct captures primarily *current* land-use preferences, this factor measures *long-term* preferences toward one's residential environment. As the statements indicate, a respondent with a higher score on this construct tends to see herself as living in an urban setting in the long term and tends not to consider a suburban setting as necessarily the best environment in which to settle down and raise children. This construct is informed by a statement shared with the prior factor (i.e. a double-loaded statement), regarding urban living in the current time frame. As before, the inclusion of the double-loaded statement produces a substantial increase in fit, further improving the validity of the overall model. As expected, the pro-urban constructs in the current and long-term time frames are positively correlated, although the magnitude of this correlation is fairly low (0.19).

2.5.3 Pro-car ownership

As discussed in Section 2.3, a substantial body of work indicates that Millennials have been bucking the upward trend on car ownership and VMT (Buchholz & Buchholz, 2012; Delbosc & Currie, 2013; Kuhnimhof et al., 2012; McDonald, 2015; Polzin et al., 2014; Sivak & Schoettle, 2011, 2012), with recent concern in the literature about the stability of this deviation (Blumenberg et al., 2012; Delbosc & Nakanishi, 2017; Garikapati et al., 2016; Lavieri et al., 2017; Newbold & Scott, 2017). In this study, this construct measures attitudes toward car ownership, with one indicator related to general attitudes toward owning material goods. A respondent with a high score on this factor tends to prefer *owning* a car, tends not to be satisfied with just having access to a vehicle when needed, and tends not to feel the need to minimize material possessions. It is pertinent to note here that we also developed and investigated a materialism construct for further analysis in this chapter (following its previous appearance in the exploratory factor analysis of the same data mentioned earlier; Circella et al., 2017b), and did find significant differences between Millennials and Gen Xers on this construct (with Millennials exhibiting greater materialism than Gen Xers, on average, consistent with their consumerist orientation as described in

Section 1.1). However, we chose not to focus on this attitudinal construct, as its causal relationship to travel behavior has not been clearly shown. Nevertheless, an indicator of the materialism construct (i.e. the general attitude toward material possessions) is retained as part of the pro-car ownership latent construct. Overall, we see that positive attitudes toward car ownership are negatively correlated with the pro-urban and pro-environmental attitudes being studied, which is conceptually reasonable as the latter constructs are associated with favorable views toward sustainable modes of transport and denser residential locations that facilitate car-free or "car-lite" lifestyles.

2.5.4 Pro-environment

Previous studies have found that Millennials tend to be more environmentally conscious than prior generations – for example, they are more likely to support environmentally-focused policies such as alternative energy (Rainie and Funk, 2015). We note that such positions are somewhat at odds with other attitudes and behavior associated with Millennials, such as materialism and the proclivity for air travel to distant experiences (Sections 2.3 and 1.1). Perhaps for this reason, the literature reports mixed results with respect to the influence of environmental consciousness on mobility decisions: while some find significant effects (Forward et al., 2010; Hopkins, 2016), with more lasting implications compared to financial or situational effects (Hopkins, 2016), others report little to no relationship between environmental attitudes and travel behavior (Anable, 2005; Delbosc & Currie, 2012). These differential conclusions may also be due to differences in sample constitution, experimental design, environmental attitude measurement, and choice of travel behavior studied. Nevertheless, in view of the clear conceptual relationships between environmental awareness and travel behavior, as well as the intriguing clash of stereotypes, we investigate differences in environmental attitudes between Millennials and Gen Xers.

As such, this construct measures a pro-environment mindset, with an emphasis on how this mindset affects transportation-related choices and behaviors. Three of the four statements measured by this construct are related to attitudes toward transportation mode and vehicle choice, while the fourth measures a general belief that greenhouse gases from human activities are creating problems. As such, a respondent with a high score on this construct tends to believe that there are environmental problems present, and tends to report being willing to alter his/her lifestyle and pay more to lead a more environmentally friendly life. We also see that this construct is positively correlated with positive views toward urban living in the present timeframe, but in line with findings from the literature, is negatively correlated with positive views toward car ownership.

2.6 *Where* is the gap?

Having introduced the attitudinal constructs that are examined in this chapter, we now analyze how each generation scores on these constructs and how large a gap, if any, exists between Millennials and Generation X in their attitudes. To this purpose, Table 3 summarizes the descriptive statistics and t-test results for differences in mean attitudinal factor scores for the generations being studied. One observation is that gaps in the mean scores for all four attitudinal constructs are not large, suggesting that generational differences in these attitudes may not be as pronounced as popular opinion has tended to portray. Nevertheless, the differences are statistically meaningful, even if modest[1]. Figure 2 provides a more fine-grained look at the differences, by splitting the Millennials cohort into younger and older segments. For three of the four attitudes studied, a clear progression in attitudes from younger to older respondents can be seen.

[1] The differences in the table are essentially Cohen's d measures of effect size (because the latent constructs are standardized), which means that the gaps identified here would be classified as small effect sizes; i.e. the mean differences shown in Table 3 have a magnitude of 0.2 or below.

Table 3 Descriptive statistics and t-tests of differences in weighted means

Attitudinal construct	Generation	N (weighted)	Mean	S.E.	Difference in Means	t-statistic[1] *(p-value)*
Currently pro-urban	Generation X	946	-0.010	0.046	-0.161	-2.58 *(0.010)*
	Millennials	1029	0.151	0.042		
Long-term pro-urban	Older Millennials[2] and Generation X	1490	-0.093	0.035	-0.149	-2.19 *(0.029)*
	Younger Millennials[2]	485	0.056	0.059		
Pro-car ownership	Generation X	946	0.037	0.047	0.195	3.15 *(0.002)*
	Millennials	1029	-0.158	0.039		
Pro-environment	Generation X	946	0.043	0.047	-0.149	-2.39 *(0.017)*
	Millennials	1029	0.192	0.040		

[1] t-test statistic corresponding to differences in means between generations.
[2] Younger Millennials represent those aged 18-25, while older Millennials represent those aged 26-34 years, all numbers relative to 2015 when the survey data was collected. As further discussed in the text, the generational divides reported in this table are those that are significant, and which will, accordingly, be decomposed in the next section.

As Table 3 illustrates, consistent with stereotype, Millennials on average have more favorable views toward currently living in urban locations, while Generation X has less favorable views. The t-test on the difference in means between generations shows the gap to be statistically significant, implying that the -0.161 gap between the mean factor scores can be validly decomposed. Further dissection of the Millennials cohort on this construct, as demonstrated in Figure 2, shows that “younger” Millennials (18-25 years old) have a larger mean factor score (0.215) compared to the “older” Millennials (26-34 years old), whose factor score averages at 0.093 (thus putting older Millennials between younger Millennials and Gen X on the attitudinal “continuum”).

Long-term attitudes toward one's living environment did not prove to be significantly different between Millennials and Generation X, but when we separated the younger Millennials (as previously demarcated) from the others, there was a more defined change. Younger Millennials, per Table 3 and Figure 2, have a positive mean factor score, while older Millennials aggregated with members of Gen X have an almost equal negative mean factor score. The similarity between older Millennials (-0.100) and Gen X (-0.091) in this construct (both having negative mean scores) resembles the findings for the currently pro-urban construct previously discussed, in that it suggests a state of attitudinal transition. Based on the relationships shown in the figure, to investigate the drivers of this gap, for this variable we combine older Millennials with Gen Xers, and decompose the statistically significant -0.149 difference in the mean values of the long-term urbanite attitude for that group versus the younger Millennials.

Attitudes regarding the desire to own a car are significantly different between the two generations (mean gap of -0.195), with Millennials indicating that on average they are more averse to owning a personal vehicle, despite their tendencies to be actually more materialistic in general (Circella et al., 2017b). For this construct, as Figure 2 shows, the mean factor score for younger Millennials (-0.224) is more negative (*farther* from the Gen X mean of 0.037) than that of older Millennials (-0.099). Regarding environmental views between the two generations per se, we again see a statistically significant difference in attitudes (-0.149), with Millennials being more environmentally conscious on average. For this variable, the difference between younger and older Millennials is relatively small, and not statistically significant.

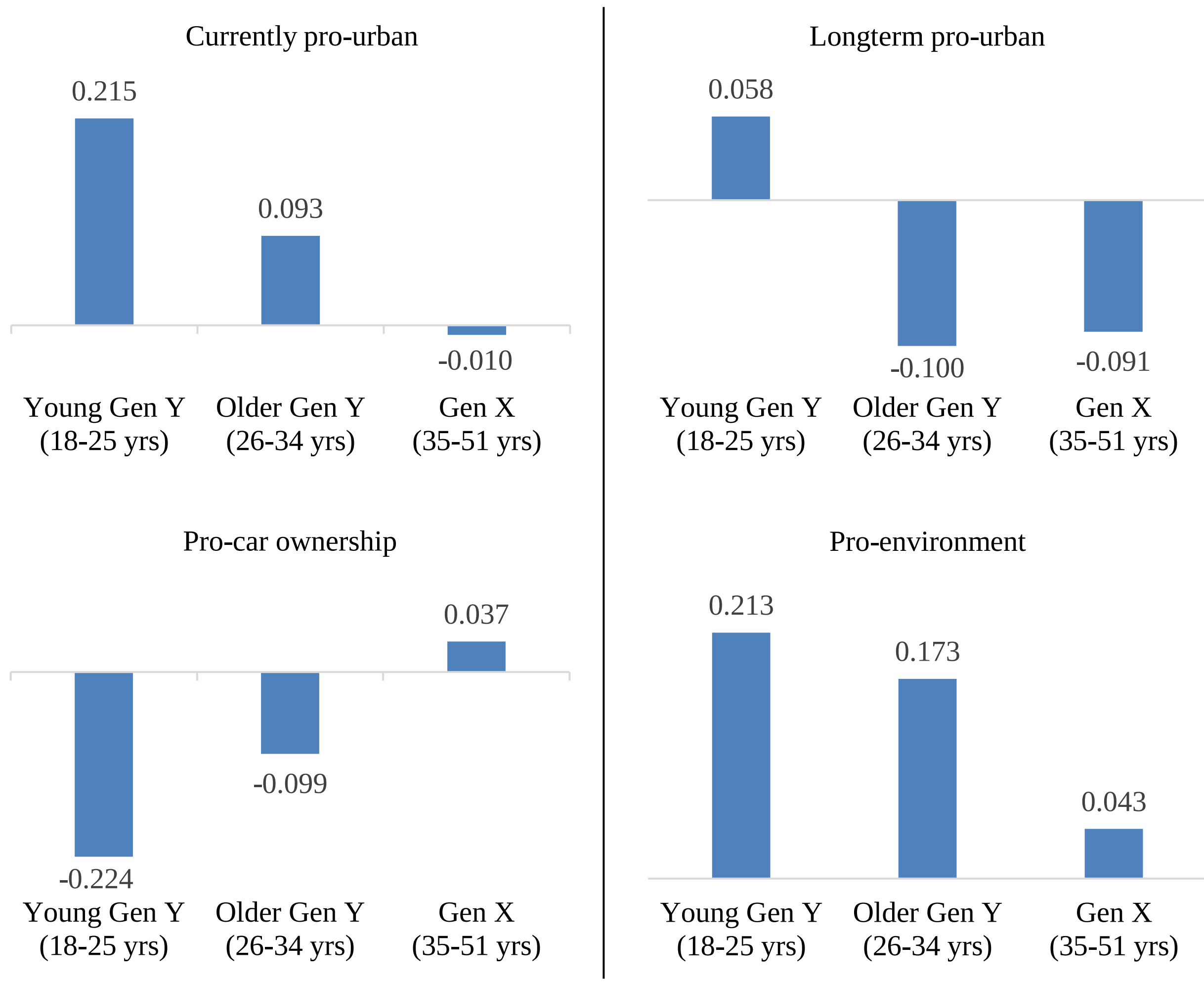


Figure 2. Detailed comparison of mean attitudinal values among generations

Based on the findings discussed here, attitudinal gaps between Millennials and Generation X are further analyzed for residential location choice attitudes in the present time frame, as well as for attitudes toward car ownership and the environment. However, for the long-term urban residential choice construct, we decompose the gap between younger Millennials and the aggregate group of older Millennials and Generation X instead, for reasons explained above. As mentioned earlier, the statistics discussed here illustrate a general trend across constructs whereby older Millennials tend to have mean factor scores that are between those of younger Millennials and Generation X, reinforcing expectations that many transport-related attitudes (and thus, observed behaviors) may exist along an age and/or life stage-related continuum.

With that in mind, it is reasonable to ask, why not simply incorporate age as a continuous explanatory variable in a regression model for each attitude, interacted with at least some of the other variables in the model? Why artificially dichotomize a continuous variable, thereby throwing away considerable information about its effects? We readily acknowledge the advantage of this alternative approach, and do not assert that our approach is unequivocally superior. Rather, we suggest that it has advantages of its own. First, for better or worse, it is common to analyze generations as discretely-defined cohorts rather than as falling along an age-based continuum, and so this study provides insight that is directly useful to this popular paradigm. Second, the gap decomposition approach clarifies and quantifies the sources of attitudinal differences more readily than would a regression model with continuously varying age and age interaction terms. Third, the present context offers a convenient and topical platform from which to highlight a methodology that, although little-used in transportation to date, has numerous potential applications in our field.

2.7 Decomposing the gap

We are often interested not only in finding differences (i.e. “gaps”) in observations over time or across groups, but also in finding the drivers (i.e. significant explanatory variables) of these differences. Going a step further requires us to ask, what are the *differential effects* of these explanatory variables on groups between which gaps have been identified? Ensuing from the seminal works of Oaxaca and Blinder (Blinder, 1973; Oaxaca, 1973), the Blinder-Oaxaca (BO) decomposition methods have been most widely applied in economics to study discriminatory behaviors of employers resulting in gender wage gaps. The gender wage gap disparity is a favored application because it is clear that while there is a plethora of *explanatory variables* (such as differing levels of education) contributing to wage differences between genders, it is also true that the *return* for men with the *same* level of a variable like education is often greater, due to discriminatory practices against women. Because the BO method has not been widely used in transportation, we next provide a detailed overview of the method.

2.7.1 Blinder-Oaxaca decomposition method

We start with the common formulation of linear regression models, with variable Y (in our case, each of the four attitudinal factor scores, respectively) modeled separately for two groups, A and B:

$Y_A = X_A' \beta_A + \varepsilon_A$ and

$$Y_B = X_B' \beta_B + \varepsilon_B \ . \tag{1}$$

Since the expected value of the error terms in a linear regression containing a constant term will be zero, the difference between the mean values of the dependent variable across the two groups can be evaluated as:

$$\Delta E(Y) = E(X_A)'\,\beta_A - E(X_B)'\,\beta_B\ . \tag{2}$$

All versions of the BO decomposition existing in the literature start from Eq. (2), and aim to rearrange and group the terms in a way that is conducive to better interpretation. The dominant decomposition philosophy is to try to understand which part of the gap in the outcome means (i.e., $\Delta E(Y)$) can be attributed to the difference in *characteristics* of each group (the explanatory variables), and which part may be attributed to the difference in the *returns* on (effects of) these characteristics (model coefficients). Following this philosophy, one may rewrite the sample version of Eq. (2) (i.e., replacing $E(X)$ with $\bar{X}$, and similarly for Y) using three terms:

$$\Delta\bar{Y} = (\overline{X_A} - \overline{X_B})'\beta_B + \overline{X_B}'(\beta_A - \beta_B) + (\overline{X_A} - \overline{X_B})'(\beta_A - \beta_B)\ . \tag{3}$$

Eq. (3) is known as the BO threefold decomposition written with respect to group B (the total mean difference could similarly be decomposed with respect to group A[2]; Jann, 2008). In other words, group B's mean outcome (level of the dependent variable) is viewed as the baseline, and we are imagining, in effect, what it would take for the reference group B's mean outcome to converge to that of group A. In the context of the present study, group B represents Millennials today, and we are investigating what it would take for their mean

[2] In that case, the proportions of the total gap associated with each of the three effects discussed below would differ, although the total gap itself would, of course, remain the same (with the sign reversed).

attitudes to converge to those of Gen Xers (group A). We discuss each term of Eq. (3) in turn.

The first term in the decomposition shows the part of the gap related to *group differences in the explanatory variables* or *endowments* (E) and is weighted by the vector of coefficients of group B. In other words, this term denotes *the mean change in the level of the dependent variable of group B (Millennials) if this group had the values of the explanatory variables of group A (Gen Xers) (while holding its coefficients constant).* The second term shows the portion of the gap stemming from the *difference in the group coefficients* (C) and, weighted by group B's vector of mean explanatory variables, indicates *the mean change in the outcome of group B if it had the coefficients of group A (while holding its endowments constant).* The final term denotes the portion of the total gap that exists due to the *interaction* (I) of differences in endowments and coefficients between the two groups. In other words, the interaction term indicates the (incremental) portion of the gap that occurs when both the endowments and coefficients change simultaneously; *or*, alternatively, the portion of the gap that remains after controlling for the endowment and coefficient portions (i.e. the all-else-equal terms: the endowment contribution while holding the respective coefficients constant, and vice versa).

The interaction term is less conducive to a simple interpretation than the first two terms, and researchers often disregard it in their analysis. However, we believe it is important not to neglect it, especially when – as is the case for us – it may account for a sizable fraction of the gap, and neglecting it therefore provides a substantially incomplete picture of the influences of the endowments and coefficients. One may interpret the interaction term as the differential effect of the change in endowments as β goes from β_B to β_A (as shown in Eq. (4)), or similarly as the differential effect of the change in coefficients as the endowment goes from $\overline{X_B}$ to $\overline{X_A}$ (as shown in Eq. (5)):

$$(\overline{X_A} - \overline{X_B})'(\beta_A - \beta_B) = (\overline{X_A} - \overline{X_B})'\beta_A - (\overline{X_A} - \overline{X_B})'\beta_B \tag{4}$$

$$= \overline{X_A}'(\beta_A - \beta_B) - \overline{X_B}'(\beta_A - \beta_B). \tag{5}$$

Combining Eq. (4) with Eq. (3), we see that the *endowment effect* – the first term on the right-hand side (RHS) of Eq. (3) – is the group B "baseline endowment effect", while Eq. (4) is the *incremental change from the group B baseline endowment effect* if group B's *coefficients as well as its endowments* changed to match group A's. Alternatively, putting Eq. (5) together with Eq. (3), we see that the *coefficient effect* – the second term on the right-hand side (RHS) of Eq. (3) – is the group B "baseline coefficient effect", while Eq. (5) is the *incremental change from the group B baseline coefficient effect* if group B's *endowments as well as its coefficients* changed to match group A's.

If the interaction effect were zero, it would mean that the magnitude of the endowment effect does not differ by group, i.e. (from Eq. (4)) that:

$$(\overline{X_A} - \overline{X_B})'\beta_A = (\overline{X_A} - \overline{X_B})'\beta_B. \tag{6}$$

Put another way, it would signify that the mean change in the level of the dependent variable if group B "ended up with" the values of the explanatory variables of group A (while holding its coefficients constant) is the same as the mean change in the level of the dependent variable if group A had "started out with" the values of the explanatory variables of group B (while holding its coefficients constant).

Alternatively, a zero interaction effect would mean that the coefficient effect does not differ by group, i.e. (from Eq. (5)) that:

$$\overline{X_A}'(\beta_A - \beta_B) = \overline{X_B}'(\beta_A - \beta_B). \tag{7}$$

In other words, it would indicate that the mean change in the level of the dependent variable if group B "ended up with" the coefficients of group A (while holding its endowments constant) is the same as the mean change in the level of the dependent variable if group A had "started out with" the coefficients of group B (while holding its endowments constant).

In contrast to the threefold approach, one common version of the BO decomposition expresses the difference between means using *two* terms, and therefore is called a twofold decomposition. Starting from the sample version of Eq. (2), we may once more rearrange the terms to arrive at Eq. (8):

$$\Delta\bar{Y} = (\overline{X_A} - \overline{X_B})'\beta_B + \overline{X_A}'(\beta_A - \beta_B)\ . \tag{8}$$

The first term of the twofold decomposition is identical to that of the threefold approach, and captures the portion of the difference in the means which is attributable to the characteristics or the explanatory variables/endowments (also known as the *quantity effect* or *explained portion*), which is weighted by the vector of coefficients of group B. The second term (also known as the *unexplained* or *discriminatory portion*), captures the difference in the coefficients, including the difference in the constant terms of the two groups (terms that capture the mean effects of *unobserved* variables and are also called group membership effects), and is weighted by the vector of mean explanatory variables in group A. The twofold approach of Eq. (8) is, in fact, a specific case of a general twofold decomposition approach popular in discrimination literature, where β^* denotes a vector of coefficients from a "non-discriminatory" model, i.e. a benchmark against which *both* groups are evaluated:

$$\Delta\bar{Y} = (\overline{X_A} - \overline{X_B})'\beta^* + \{\overline{X_A}'(\beta_A - \beta^*) + \overline{X_B}'(\beta^* - \beta_B) \tag{9}$$

As special cases of Eq. (9), if we consider either of the groups as the one with no discrimination, i.e. $\beta^* = \beta_B$ or $\beta^* = \beta_A$, we arrive at the simpler form of the twofold decomposition shown in Eq. (8). However, when it is not clear that a particular group should be treated as the point of reference, the non-discriminatory model in Eq. (9) is considered the benchmark against which the two groups are evaluated, and is often executed as a pooled model across groups. The choice of the non-discriminatory model, however, is a point of contention, with scholars proposing different methods of selecting a comparative model. Reimers (1983), for instance, proposed the vector consisting of the unweighted mean of β_A and β_B to be used as β^*, while some scholars (ex. Jann, 2008) recommend using the pooled regression model, but including the variable segmenting the two groups so as to avoid inappropriate inflation of the explained part of the decomposition.

The literature offers scant advice regarding a suitable choice of BO decomposition method. A common point of contention with twofold decomposition methods, however, is that the interaction term is not separated from the endowment (group differences) and coefficients (effect differences), even though there is little reason not to separate this term from the other two (Biewen, 2014). In addition, the threefold decomposition provides a more consistent interpretation with respect to the reference group, with both the endowment and coefficient terms stating, respectively, how the reference group mean outcome would change if it had the mean characteristics or coefficients of the non-reference group. The same consistency in interpretation, however, does not happen with twofold decomposition, with the explained and unexplained portions not using the same reference group with which to weight the terms. On the other hand, the interpretation of twofold decompositions has often proven to be more straightforward, specifically in cases where the interaction term in the threefold decomposition proves to be a significant portion of the gap – but we would argue that such instances are precisely those in which the more explicit decomposition of the threefold method is most important.

2.8 Results and discussion

In this study, we apply the threefold BO decomposition (Eq. (3)) to investigate generational differences in attitudes[3]. As discussed, this method presents a more fine-grained decomposition by separating the interaction term from the other two terms, thus allowing for a more consistent and "cleaner" interpretation. We select Millennials as the

[3] The Oaxaca package (Jann, 2008) in Stata version 15.1 was used to execute this analysis.

reference group, and thus, the results should be interpreted as representing how Millennials' mean attitudes would change if they only had Generation X characteristics (endowments) or if Millennials' own characteristics were only influenced to the same extent that Gen Xers' characteristics were (coefficients), or if both effects occurred at once (interaction). In principle, this allows us to separate the portion of the gap that is attributable to Millennials currently just being at a different life stage (part of their endowment), from that which is due to more fundamental shifts in effects (coefficients) that may persist even after (if) their endowments converge to those of Gen Xers. In reality, however, the constant term of each model captures the average impact of all relevant *unobserved* variables on the associated attitude, and as such, the composite contributions of those variables to the gap are accounted for as a difference in the constant term between cohorts. Although this is technically a difference in coefficient, in actuality the constant term will include (average) unobserved *endowments*, together with their coefficients. If the Millennials' constant term were to approach that of Gen Xers' over time, it would be unknown whether this were due to both *unobserved endowments* and the *coefficients of those endowments* converging, or whether changes in one of those things narrowed the gap while changes in the other widened it (but with the first effect predominating).

The segmented linear regression models are estimated using sociodemographic and (when appropriate[4]) built environment characteristics, as these variables facilitate clearer interpretation of life-stage effects and are less likely than behavioral or other attitudinal variables to be endogenous. We first estimate segmented models (for Millennials and Generation X) for each construct, and identify significant explanatory variables across the two regression models. We then test all identified significant variables in the decomposition model. To better focus on the decomposition results, we present the fully estimated models and more detailed discussion on the impact of the significant variables in Appendix A, and bring only an overview of the models into the following sections. As a general observation, it should be noted that the R^2 goodness-of-fit measures for the models – i.e., the proportions of variance in attitudes that are explained by observed variables – are fairly modest (ranging from 0.058 to 0.143), albeit consistent with typical values for disaggregate travel behavior-related models. Nevertheless, as just indicated, the composite contributions of the remaining, *unobserved* variables to the gap are accounted for as a difference in the constant term between cohorts.

Table 4 provides a summary of the decompositions for the four attitudes studied in this chapter. In the following sections we discuss these results in greater detail. In addition,

[4] Built environment variables were not included in the equations for currently pro-urban attitude to avoid potential endogeneity. Accessibility measures such as *Walk Score®* or *Bike Score® indices*, the inclusion of which could potentially result in the same endogeneity problem, were nevertheless tested for all models (because there were conceptual grounds for inclusion) but their effects were not found to be statistically significant.

Section A.2 in Appendix A provides decomposition results aggregated by variable type, to better summarize the overall impact on the attitudinal gaps of the life-stage variables in particular.

Table 4 Summary of decomposition of attitudinal gap results

Attitudinal construct	Generation	Mean	Gap	Endowment	Coefficient	Interaction
Currently pro-urban	Generation X	-0.010	-0.161 100%	-0.052 32%	-0.048 30%	-0.061 38%
	Millennials	0.151				
Long-term pro-urban	Older Millennials and Generation X	-0.093	-0.149 100%	-0.265 178%	-0.019 13%	0.135 -91%
	Younger Millennials	0.056				
Pro-car ownership	Generation X	0.037	0.195 100%	0.082 42%	-0.032 -16%	0.145 74%
	Millennials	-0.158				
Pro-environment	Generation X	0.043	-0.149 100%	-0.047 32%	-0.052 35%	-0.050 33%
	Millennials	0.192				

2.8.1 Currently pro-urban attitude

The segmented regression results for the currently pro-urban attitude, detailed in Section A.1 of the Appendix A, associate life-stage variables such as being married and having higher income with a lower pro-urban tendency, while employment status shows a positive association. In addition, female Millennials tend to be significantly less pro-urban than their male counterparts, a trend that is not present (or significant) for Gen Xers. Moreover, Millennials who have a parent (or parents) with graduate-level education tend to be more pro-urban, while this influence is the opposite (though not significant) with Gen Xers, potentially pointing to a critical generational difference in how those raised in well-educated (higher-earning) households view the desirability of living in urban areas. With regard to race, Native Americans tend to be less pro-urban, while Asians tend to be more pro-urban, relative to other races.

Based on these regression results, Table 4 shows the threefold decomposition of the gap between the mean currently pro-urban attitudes of Millennials and Gen Xers. The total gap for this attitude (Table 2) is -0.161 (standard deviations), with the three decomposition portions explaining approximately equal shares of this gap (i.e. ~ -0.05 each). The endowment term, itself only marginally significant at a 10% level, includes several significant (at the 10% level) life-stage and political affiliation variables, while gender, race, and childhood residential location appear to explain little of the overall endowment portion of this decomposition. Similarly, the coefficient term, while itself not statistically significant, contains significant contributions associated with variables such as gender, marital status, parental education, and political affiliation. To provide a more intuitive basis for interpretation, Figure 3 and Figure 4 show the detailed contributions of each variable to the endowment and coefficient portions of the currently pro-urban attitudinal gap, respectively; each bar shows the contribution (in standard deviation units) associated with each variable, in addition to its 95% confidence interval.

Table 5 Detailed threefold decomposition for the currently pro-urban attitude

	Endowment		Coefficient		Interaction		Total
	Coef. (Std. Err.)	p-value	Coef. (Std. Err.)	p-value	Coef. (Std. Err.)	p-value	Coef.
Raised in Hawaii	-0.003 (0.006)	0.622	-0.010 (0.006)	0.108	0.003 (0.006)	0.621	-0.010
Raised in Northeast	0.001 (0.002)	0.766	0.013 (0.008)	0.114	0.004 (0.005)	0.447	0.018
Native American	0.005 (0.005)	0.356	-0.0003 (0.011)	0.975	0.0001 (0.003)	0.975	0.005
Asian	-0.003 (0.005)	0.579	0.019 (0.025)	0.453	0.001 (0.003)	0.649	0.017
Female	-0.001 (0.006)	0.882	0.109 (0.062)	0.079	0.001 (0.007)	0.882	0.109
Married	-0.019 (0.024)	0.440	-0.097 (0.048)	0.044	-0.076 (0.038)	0.047	-0.192
High household income (> $100K)	-0.032 (0.018)	0.067	0.012 (0.041)	0.765	0.007 (0.024)	0.765	-0.013
Parent w/ graduate education	0.004 (0.006)	0.556	-0.074 (0.032)	0.019	-0.006 (0.010)	0.555	-0.076
Employed	0.011 (0.006)	0.081	-0.059 (0.097)	0.543	-0.005 (0.009)	0.549	-0.053
Democrat	-0.001 (0.003)	0.748	0.083 (0.056)	0.137	-0.005 (0.007)	0.464	0.077
Republican	-0.020 (0.011)	0.074	0.050 (0.024)	0.040	0.014 (0.010)	0.156	0.044
Constant	-	-	-0.093 (0.157)	0.552	-	-	-0.093
Total	-0.052 (0.031)	0.100	-0.048 (0.067)	0.473	-0.061 (0.042)	0.148	-0.161

2.8.1.1 Endowment

As shown in Figure 3, disparities in generational shares of high-income groups, political affiliation, employment status, and marital status contribute the most to the overall endowment portion of the gap, although the contribution of disparity in marital status shares is not statistically significant, despite its magnitude. Those in higher-income households tend to have less favorable currently pro-urban attitudes (see regression results in Appendix A); therefore, with Millennials currently lagging in earnings compared to Gen X, we may expect their favorability toward currently pro-urban living to drop by as much as 0.032 (standard deviation units) if (all else equal) the Millennials' share of high income (>$100K) households matched Gen Xers' current share. In other words, the younger generation's attitude toward currently pro-urban living could close the gap (through becoming less pro-urban) by as much as 20% (-0.032 / -0.161 = 0.20) given these conditions. On the other hand, being employed has a positive effect on this attitudinal construct (see regression results in the Appendix A), suggesting that if the employment rate among Millennials were to match that of their older peers (as they graduate and enter the workforce), they may on average (holding all else constant) become slightly more pro-urban (+0.011 s.d. units), thereby *widening* the gap by 7%. With regard to marriage rates, we see that if Millennials were to have the same shares of marriage as Gen Xers, their favorability toward currently pro-urban living (all else equal again) would decrease by 0.019 s.d. units (narrowing the gap by 12%).

Considering the overall impact of the life-stage variables discussed, the model suggests that there may be an overall 0.039 s.d. (roughly 25%) decrease in the gap (due to Millennials becoming less pro-urban) as more Millennials enter the workforce, marry, and ultimately earn higher incomes (see Appendix A.2). Such predictions, needless to say, assume the temporal invariance of the Millennials' model coefficients. In other words, it assumes that as Millennials continue to age, their currently pro-urban attitudes will be *influenced* by these life-stage variables in a similar way as they are now, even though the *measured values* of these variables are changing. Testing the validity of these assumptions requires longitudinal data, and as with many other models in practice and literature, such insights into the future based on cross-sectional data should be interpreted with due caution.

Finally, we see (from its coefficient in Table A.1 in Appendix A) that those who identify as Republican have lower tendencies to be pro-urban and this party also has lower shares in the Millennials generation (Table 2), a disparity that accounts for approximately 38% (-0.020/-0.052) of the endowment gap and 12% of the total gap.

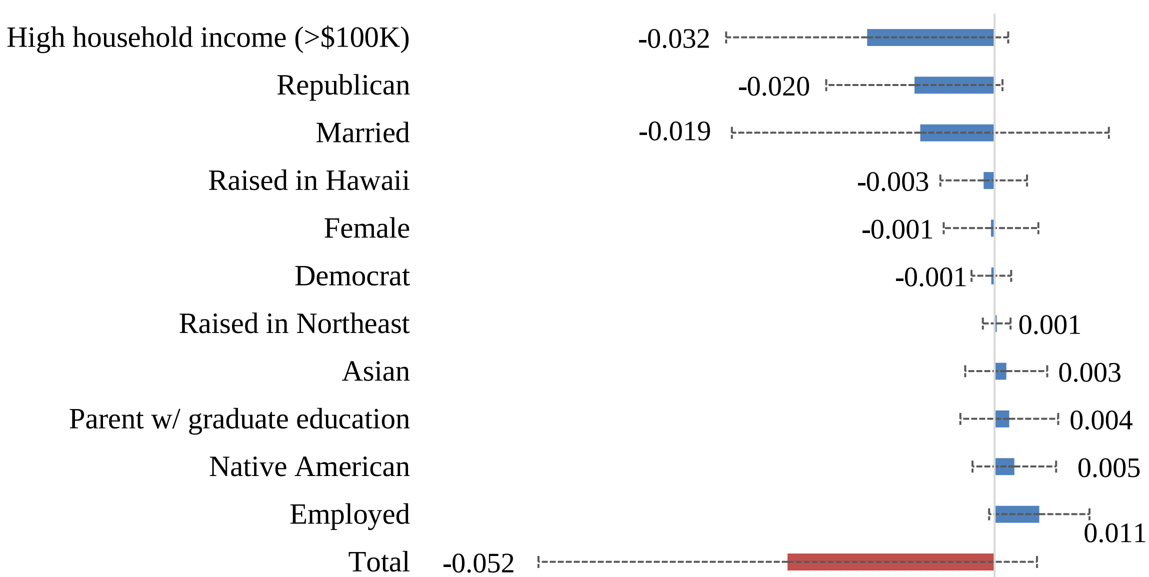


Figure 3 Contributions to the endowment portion of the difference in mean "currently pro-urban" attitude. (Horizontal dashed lines portray the 95% confidence interval)

2.8.1.2 <u>Coefficient</u>

Figure 4 details the coefficient portion of the gap, with effect disparities of marital status, parental education level, political affiliation, and gender having relatively large and significant contributions to the overall coefficient portion. Although both generations tend to be less pro-urban when married (see Appendix A.1.1), this effect is stronger among Gen Xers, hence the decrease (all else equal) in Millennial's average "currently pro-urban" attitude if marriage were to influence *their* attitude similarly to the way it influences Gen Xers'. Meanwhile, Millennials having a parent with graduate-level education tend to be more "currently pro-urban", while Gen Xers with the same characteristics show the opposite effect, and so if Millennials had the coefficients of Gen X on these attributes, there would again be decreases in their overall attitude toward urban living. Finally, we see that right-leaning political affiliations and gender (being female) both have a stronger negative effect on the pro-urban attitude among Millennials, hence, in this case if Millennials had the coefficients of Gen X on these attributes, there would be *increases* in their overall affinity for urban living. Thus, as illustrated in this discussion, the BO method facilitates an examination of not only the *variables* that are affecting pro-urban attitudes, but also the role of differential *effects* of the explanatory variables on the identified attitudinal differences between generations.

In Appendix A.2, as mentioned, we further discuss the aggregated effect (by life-stage variables and other characteristics) of the three terms, pointing out that, although the total coefficient effects are generally smaller than the endowment effects, the *life-stage* coefficient effects per se tend to be much larger than their endowment counterparts. This aggregated decomposition brings additional insight into how different groups of variables impact the gap differently.

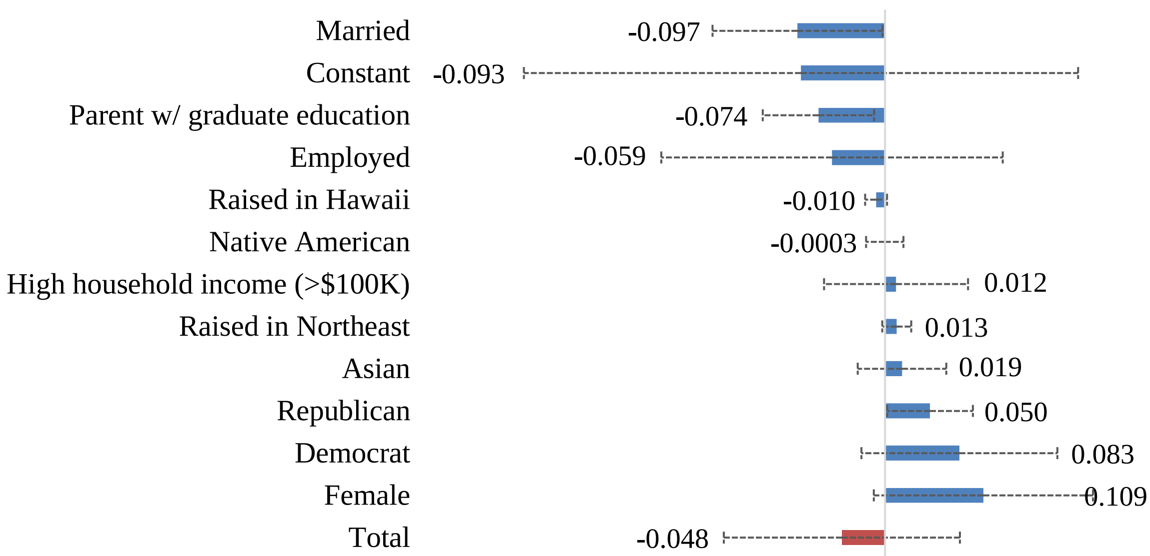


Figure 4 Contributions to the coefficient portion of the difference in mean "currently pro-urban" attitude. (Horizontal dashed lines portray the 95% confidence interval)

2.8.1.3 Interaction

With respect to the interaction term of -0.061, following the earlier discussion, we can say that (as already seen from Table 4 and Figure 3 and Figure 4): the baseline endowment effect for Millennials is -0.052 (holding their coefficients constant but changing their endowments to those of the Gen Xers); and the baseline coefficients effect for Millennials is -0.048 (holding their endowments constant but changing their coefficients to those of the Gen Xers); but an *additional* effect of -0.061 is accrued if *both* their endowments and their coefficients were to change to those of the Gen Xers at the same time. The relative magnitude of this interaction effect (it is the largest component of the gap, accounting for 38% of it) demonstrates its importance.

We can also interpret the specific contribution of the most important variable in the interaction effect, namely marital status. As previously discussed, if Millennials were to achieve the *same marriage rate* as Gen Xers while keeping all coefficients constant (the *endowment* effect), the mean contribution to the total gap of -0.161 would be -0.019, closing it by 12%. If marital status were to have the same *effect* on the currently pro-urban attitude for Millennials as for Gen Xers while not changing their actual marriage rates (the *coefficient* effect), the mean contribution to the gap would be -0.097, closing it by 60%. But if *both* the marriage *rate* and the *effect of marital status* for Millennials converged to those of Gen Xers, the *additional* contribution to the gap would be -0.076, closing it by a further 47% (the fact that the sum of these contributions exceeds 100% merely indicates that other explanatory variables contribute to *widening* the gap, as we saw with the endowment effect for employment status).

2.8.2 Long-term pro-urban attitude

As discussed in Section 2.6, the long-term pro-urban attitude is segmented based on the younger Millennials cohort (< 26 years old) relative to an aggregate group of older Millennials and Generation X. For this attitude, as detailed in Appendix A.1, we see that attributes related to childhood residential location, current residential location, race, income level, education level, political affiliation, and the interaction between marital status and children are statistically significant predictors of the long-term pro-urban attitudinal construct. Notably, among younger Millennials, those who currently live in urban areas tend to have significantly more favorable attitudes toward long-term urban living than non-urban dwellers, an effect that is consistent but not significant for their older peers. In addition, those who identify as White in both cohorts being studied tend to have significantly more favorable attitudes toward long-term urban living relative to other races.

With regard to life stage variables, we see that the interaction of being married and number of children (in the household) is significant for both cohorts, indicating that those who are married and with more children in the household tend to have less favorable attitudes toward long-term urban living. Additionally, we see that those with lower levels of education and income show a more favorable opinion toward living long-term in urban environments.

Based on these regression results, Table 6 presents the decomposition of the difference in means for the long-term urbanite attitude (-0.149). We see that the endowment portion of the gap is the largest, with the interaction portion cancelling out roughly half of its negative value. The magnitude of the interaction term here is mostly due to the "married × number of children" term, with the other interaction effects significantly smaller. This illustrates that the simultaneous change in the share and effect of this variable plays a large role in defining the gap in this attitude, as will be discussed further below. The overall coefficient portion is significantly smaller than the endowment and interaction portions, with none of its terms having large magnitudes or showing statistical significance. As before, Figure 5 and Figure 6 visually illustrate the endowment and coefficient portions of the long-term urban living gap to allow for a more intuitive interpretation of Table 6.

Table 6 Detailed threefold decomposition for the long-term pro-urban attitude

	Endowment		Coefficient		Interaction		Total
	Coef. (Std. Err.)	P-value	Coef. (Std. Err.)	P-value	Coef. (Std. Err.)	P-value	Coef.
Raised in the Southeast	0.015 (0.012)	0.223	-0.021 (0.013)	0.100	-0.022 (0.015)	0.139	-0.028
Raised in Hawaii	-0.002 (0.005)	0.661	-0.006 (0.006)	0.296	0.002 (0.005)	0.661	-0.006
Raised in Alaska	-0.009 (0.010)	0.352	-0.010 (0.01)	0.303	0.008 (0.009)	0.380	-0.011
White	0.013 (0.011)	0.250	-0.047 (0.068)	0.491	-0.005 (0.007)	0.541	-0.039
Number of children	0.023 (0.041)	0.571	-0.013 (0.064)	0.841	-0.010 (0.052)	0.841	0.000
Married×No. of children	-0.280 (0.107)	0.009	0.038 (0.027)	0.157	0.177 (0.119)	0.138	-0.065
Married	0.051 (0.090)	0.569	-0.0001 (0.035)	0.998	0.003 (0.031)	0.934	0.054
Low household income	-0.045 (0.028)	0.103	-0.006 (0.067)	0.934	-0.0003 (0.099)	0.998	-0.051
High school education only	-0.019 (0.020)	0.328	0.023 (0.044)	0.610	-0.013 (0.025)	0.612	-0.009
Urban dweller	-0.0001 (0.001)	0.908	0.053 (0.048)	0.269	-0.001 (0.007)	0.865	0.052
Republican	-0.012 (0.010)	0.211	-0.004 (0.017)	0.798	-0.003 (0.012)	0.798	-0.019
Constant	-	-	-0.026 (0.145)	0.855	-	-	-0.026
Total	-0.265 (0.086)	0.002	-0.019 (0.075)	0.796	0.135 (0.092)	0.143	-0.149

2.8.2.1 Endowment

With respect to the baseline endowment effect, Figure 5 shows that by far the strongest influence belongs to the interaction of marital status with number of children in the household, but this term should be interpreted in conjunction with its constituents, the marital status and number of children variables. The interpretation is that if younger

Millennials were to have the same share of married people, the same average number of children, and the same average number of children per married person as the older group does (holding all else constant), they would have a significantly less favorable attitude toward living long-term in urban environments. With respect to other life-stage variables, we see that the contributions of having a lower income (relatively large, although not statistically significant) and only a high school level education suggest that younger Millennials' views of long-term urban living will become less favorable as they graduate from college and increase their earnings.

The combined contributions of these life-stage disparities add to 0.270 overall (Table A.6 in Appendix A), accounting for 181% of the total gap of -0.149. This implies that if younger Millennials took on the same life-stage endowments as their older peers but kept their own coefficients (and all else constant), they could end up even less favorable toward long-term living in urban areas than the older group is now. However, note from the coefficient and interaction effects of these variables (shown in the aggregate in Table A.6, in the disaggregate in Table 6, and discussed below) that if the younger Millennials' coefficients also changed to those of the older group, the net effect of the four life-stage variables (low income, high school education, married, and number of children, plus the interaction of the last two) on attitudes would be -0.072, closing just 48% of the gap rather than "overshooting" it.

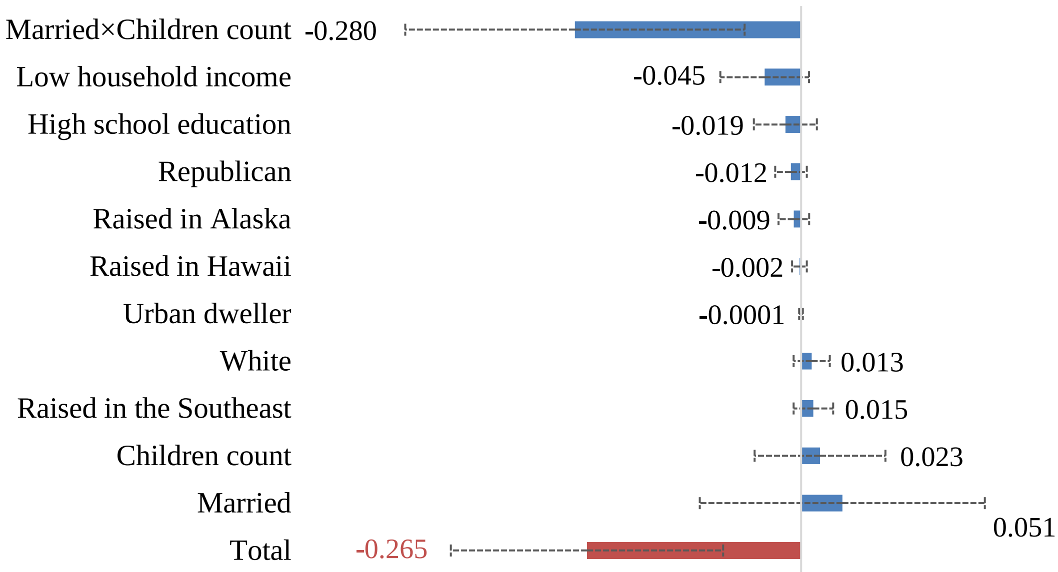


Figure 5 Contributions to the endowment portion of the difference in mean "long-term pro-urban" attitude. (Horizontal dotted lines refer to the 95% confidence interval)

2.8.2.2 Coefficient

Figure 6 portrays the coefficient portion of the gap; however, none of the effect disparities are statistically significant nor practically large, and we therefore do not discuss the results of this portion further.

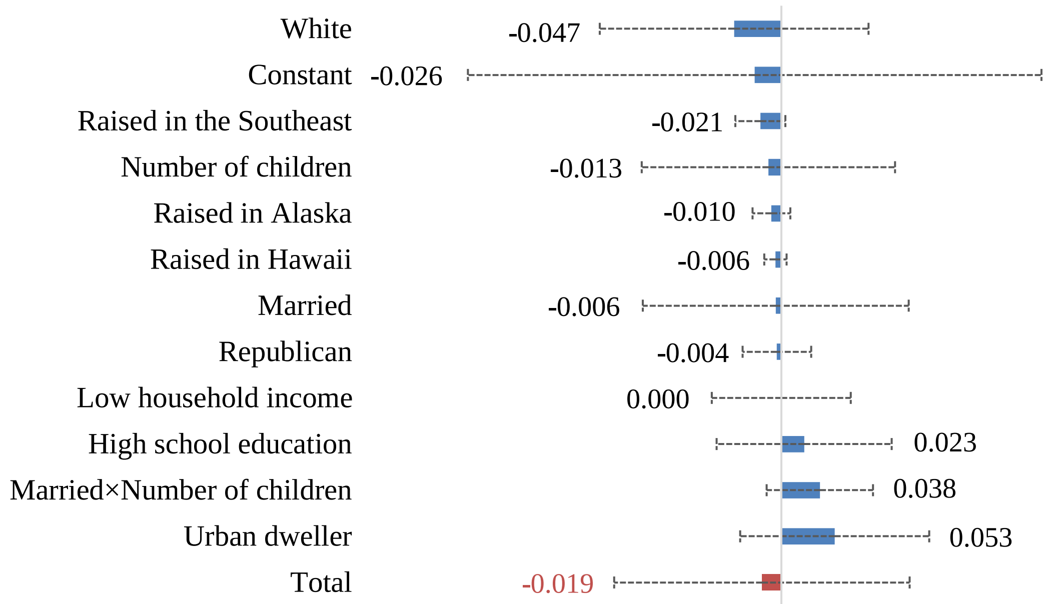


Figure 6 Contributions to the coefficient portion of the difference in mean "long-term pro-urban" attitude. (Horizontal dashed lines refer to the 95% confidence interval)

2.8.2.3 Interaction

The interaction term here has a relatively large contribution, and as discussed, indicates an incremental effect of 0.135 s.d. units that substantially counteracts the baseline endowment and coefficient effects when *both* endowments and coefficients of younger Millennials change to those of their older peers at the same time. The large magnitude of this term can mostly be attributed to the "married × number of children" variable. Considering this variable together with its main-effects constituents, we see that if *both* the *means* and the *effects* of these variables (married, number of children, and their interaction) for younger Millennials converged to those of the older group, the *incremental* contribution (on top of endowment and coefficient effects) to the gap would be 0.170. However, it is best to consider the interaction effect *together* with the endowment and coefficient effects: the total effect of these three variables is a scant -0.011, indicating that the net impact on the gap of this bundle of variables, if both endowments and coefficients of the younger Millennials achieved those of the older group, would be negligible (closing only 7% of the -0.149 gap). Viewed this way, the other two life-stage variables, low income and high school education, are more powerful: the total combined effects of these two variables is -0.0603, which would close 40% of the overall gap if the younger Millennials replicated the income and education endowments and coefficients of their older counterparts.

2.8.3 Pro-car ownership attitude

As shown in Appendix A.1, the significant variables in the regression models for the pro-car ownership attitude include attributes related to childhood and current residential locations, gender, race, education level, marital status, occupation, student status, and political affiliation. We see that urban dwellers tend to be less pro-car, although this effect is attenuated among Millennials. Regarding race, Whites and African-Americans tend to have more favorable views toward car ownership, while Asians have less favorable views, relative to the base group which represents all other races (Native Americans, mixed race, and others). Gender is also a significant predictor, with women tending to have more favorable car ownership attitudes than men. With respect to education, those with a high school education, and those who are college students, are less insistent on owning a car, potentially because of lower income levels and overall needs relative to those with higher education levels. Those who identify as Republican tend to have more favorable views toward owning a car, and in conjunction with previously reported results, we see that

Republicans in the sample tend to be less pro-urban, less pro-environment, and more pro-car ownership than those of other political affiliations.

We now turn to the BO decomposition for the pro-car ownership construct (Table 7). The endowment portion of the gap significantly explains 42% of the total gap, while the coefficient portion is much smaller and contributes in the opposing direction. The interaction portion in this decomposition is the largest, explaining about 74% of the gap. In the endowment portion of the decomposition, education level and student status have the largest contributions, while in the coefficient portion of the model, race, marital status, and built environment have the largest contributions. Figure 7 and Figure 8 illustrate the contributions of the explanatory variables to the endowment and coefficient portions of the gap.

Table 7 Detailed threefold decomposition for pro-car ownership attitude

	Endowment		Coefficient		Interaction		Total
	Coef. (Std. Err.)	P-value	Coef. (Std. Err.)	P-value	Coef. (Std. Err.)	P-value	Coef.
Raised in Hawaii	0.002 (0.003)	0.620	0.007 (0.005)	0.112	-0.002 (0.005)	0.622	0.009
Raised in Southeast	-0.006 (0.006)	0.315	-0.015 (0.009)	0.104	0.005 (0.005)	0.358	-0.016
Native American	0.008 (0.006)	0.161	-0.003 (0.005)	0.507	-0.002 (0.003)	0.541	0.003
White	0.001 (0.004)	0.809	0.165 (0.073)	0.024	0.014 (0.012)	0.237	0.180
African-American	0.004 (0.004)	0.379	0.007 (0.009)	0.392	0.002 (0.004)	0.521	0.013
Asian	-0.004 (0.008)	0.573	0.050 (0.030)	0.098	0.004 (0.007)	0.588	0.050
Female	0.001 (0.007)	0.882	-0.106 (0.059)	0.073	-0.001 (0.007)	0.882	-0.106
High school education only	0.026 (0.011)	0.016	0.019 (0.030)	0.528	-0.010 (0.016)	0.531	0.035
Urban dweller	-0.0001 (0.002)	0.955	-0.111 (0.041)	0.006	0.011 (0.012)	0.373	-0.100
Student	0.052 (0.020)	0.010	-0.031 (0.059)	0.598	0.023 (0.044)	0.598	0.044
Married	-0.016 (0.024)	0.494	0.119 (0.046)	0.009	0.092 (0.037)	0.011	0.195
Republican	0.014 (0.009)	0.108	0.017 (0.024)	0.492	0.005 (0.007)	0.517	0.036
Employed in service	0.001 (0.002)	0.679	0.009 (0.006)	0.169	0.003 (0.004)	0.430	0.013
Constant	-	-	-0.158 (0.169)	0.348	-	-	-0.158
Total	0.082 (0.034)	0.016	-0.032 (0.075)	0.671	0.145 (0.058)	0.013	0.195

2.8.3.1 Endowment

As shown in Figure 7, education-related variables contribute the most to the overall endowment gap, with disparities in shares of students and those with only a high school education between the two generations explaining a significant portion of the endowment gap. As before, these terms indicate that if the shares of Millennial students and those with only a high school education diminish to the Gen Xers' levels, the mean pro-car attitude among Millennials could increase by 0.052 and 0.026 s.d. units, respectively. Additionally, the disparity in marriage rates demonstrates a relatively large (although not statistically significant) contribution, albeit in the negative direction. Overall, assuming that Millennials were to end up having the same shares for these life-stage variables (and holding all else equal), we may see an increase of as much as 0.062 s.d. units (i.e. a 32% decrease in the gap) in the mean pro-car attitude of Millennials as they graduate with a college degree and begin to get married. In addition to the life-stage variables, the difference in shares of political affiliation also results in a relatively large contribution. Millennials, with a lower share of Republicans in our weighted dataset, would have a stronger pro-car attitude if they had as many Republicans as the Gen X generation does.

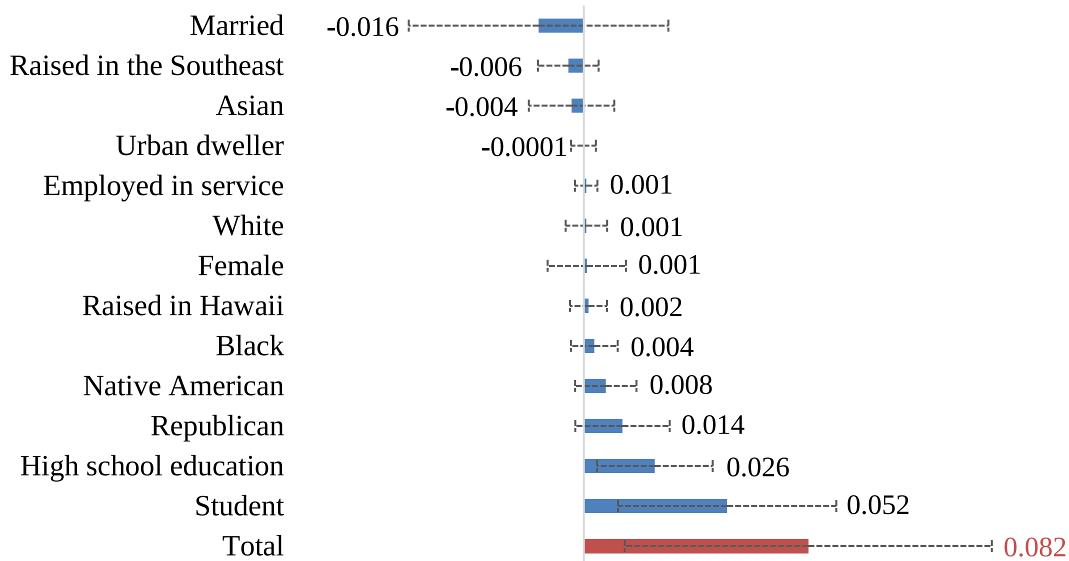


Figure 7 Contributions to the endowment portion of the difference in mean "pro-car ownership" attitude. (Horizontal dashed lines refer to the 95% confidence interval)

2.8.3.2 Coefficient

The overall contribution of the coefficient portion (Figure 8) is relatively small and insignificant, although this insignificance and low magnitude is due largely to sizable contributions in opposite directions. The constant term, which indicates the difference in the effect of unobserved variables between the two groups, has the largest, yet not statistically significant, contribution. The effect disparity of the built environment is also significant, with Gen Xers living in urban areas interestingly having a lower tendency to be pro-car than their Millennial neighbors do (perhaps suggesting that living in an urban area signifies more of a lifestyle commitment for Gen Xers, who may be married and with families, than for the more transient Millennials, who may yet move to the suburbs when they marry and have children). The effect disparity for marital status also explains a relatively large portion of the gap, showing that if being married were to have the same impact on the pro-car attitude of Millennials as it does for Gen Xers, Millennials' attitudes would become more favorable on average. Finally, race plays a significant role, specifically the differential impact on pro-car attitudes of being Asian or White that is exhibited by Millennials relative to their Generation X peers.

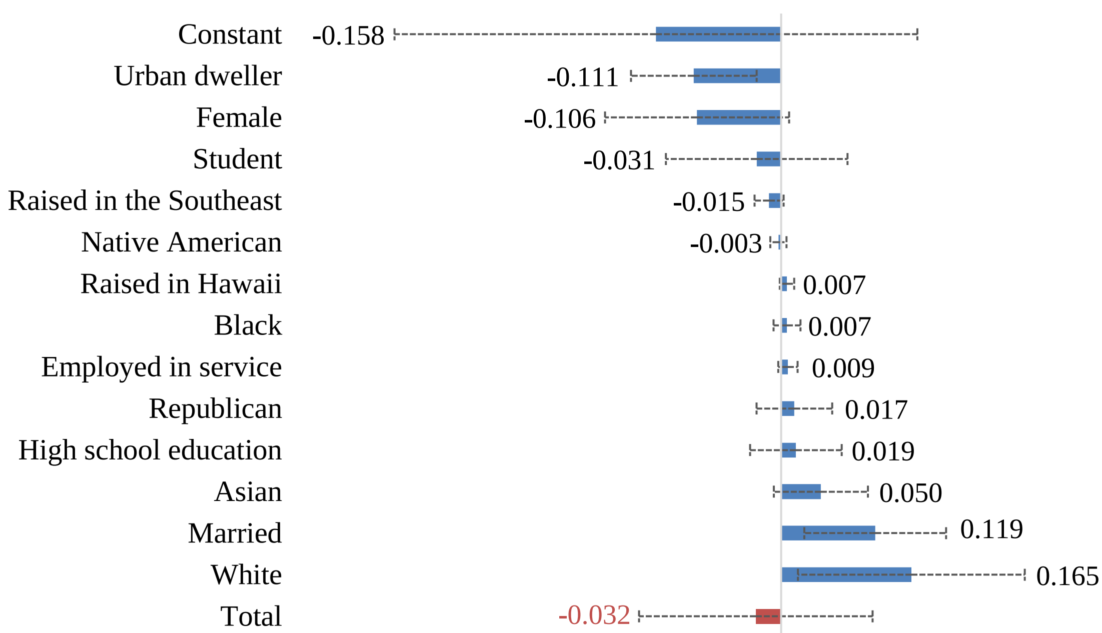


Figure 8 Contributions to the coefficient portion of the difference in mean "pro-car ownership" attitude. (Horizontal dotted lines refer to the 95% confidence interval)

2.8.3.3 <u>Interaction</u>

The interaction term has a relatively large value here (0.145), stemming largely from marital status (the only significant interaction effect). We see that the incremental effect (on top of the all-else equal terms) of the simultaneous change of endowments and coefficients for the married variable would result in a more favourable pro-car ownership attitude for the Millennials. This incremental effect is in the opposite direction to the endowment effect, but in line with the coefficient effect. The total of all three effects for the married variable essentially accounts for the entire attitude gap of 0.195 s.d. units; the effects of all other variables almost exactly cancel each other out.

2.8.4 Pro-environment attitude

The regression models for the pro-environment attitude, detailed in Appendix A.1, show that childhood residential location, current residential location, race, income level, education level, employment status, student status, and political affiliation are all statistically significant predictors of attitudes toward environmentally-conscious living. Living in an urban area tends to indicate more favorable pro-environment attitudes for both cohorts. In addition, we see that being a member of either Hispanic or Asian racial/ethnic groups is a significant predictor of environmental attitudes for both cohorts, with members of these groups tending to be more pro-environment than those from other races. Furthermore, among Millennials, those who are students, employed, or have high individual income levels (> $100K) tend to be more pro-environment than their counterparts, while for the same groups of Gen Xers, although the average effects are also positive, they are smaller and not statistically significant. This observation suggests a generational divide in which employed Millennials with or without well-paying jobs report a greater care for the environment than the preceding generation.

Table 8 below summarizes the detailed threefold decomposition of the generational difference in the mean pro-environment attitude. The total difference in mean attitude between Millennials and Generation X (Table 3) is -0.149 s.d. units. This difference is approximately equally explained by the three components of the decomposition, although the statistical significance of each term is poor. Upon closer investigation, however, we can see that these lower significance levels are largely due to statistically significant contributions of several influential variables in opposite directions that end up cancelling each other out, resulting in a smaller total contribution for each portion with consequently a lower significance level. Figures 9 and 10 show the detailed contribution of each variable to the endowment and coefficient portions of the overall difference, respectively. Given that none of the effects for the interaction term are significant or relatively large, we do not discuss those in detail here.

Table 8 Detailed threefold decomposition for pro-environment attitude

	Endowment		Coefficient		Interaction		Total
	Coef. (Std. Err.)	p-value	Coef. (Std. Err.)	p-value	Coef. (Std. Err.)	p-value	Coef.
Raised in the Pacific region	0.001 (0.002)	0.560	0.008 (0.005)	0.086	-0.002 (0.003)	0.562	0.007
Raised in Alaska	0.002 (0.002)	0.350	-0.004 (0.004)	0.298	0.003 (0.004)	0.398	0.001
Asian	0.002 (0.004)	0.587	0.053 (0.022)	0.019	0.004 (0.007)	0.578	0.059
Hispanic	-0.031 (0.014)	0.027	0.031 (0.061)	0.610	-0.011 (0.021)	0.612	-0.011
Urban dweller	-0.005 (0.006)	0.390	0.032 (0.043)	0.457	-0.003 (0.005)	0.559	0.024
High individual income (> $100K)	0.071 (0.030)	0.018	-0.027 (0.016)	0.085	-0.062 (0.036)	0.083	-0.018
Student	-0.084 (0.021)	<0.001	-0.050 (0.066)	0.446	0.038 (0.050)	0.446	-0.096
Employed	0.021 (0.008)	0.009	-0.197 (0.089)	0.027	-0.017 (0.009)	0.063	-0.193
Republican	-0.021 (0.012)	0.077	0.012 (0.028)	0.670	0.003 (0.008)	0.677	-0.006
Democrat	-0.004 (0.005)	0.440	0.044 (0.052)	0.394	-0.003 (0.005)	0.549	0.037
Constant	-	-	0.047 (0.132)	0.719	-	-	0.047
Total	-0.047 (0.041)	0.254	-0.052 (0.075)	0.486	-0.050 (0.061)	0.417	-0.149

2.8.4.1 Endowment

As Figure 9 demonstrates, significant contributors to the endowment portion of the mean attitudinal difference, i.e. contributions arising from differences in the levels of explanatory variables, are student status, employment status, high individual income levels, Hispanic ethnicity, and Republican affiliation. Focusing on non-life-stage variables first, we see that differences in shares of Republicans and Hispanics between Millennials and Gen Xers in the weighted dataset explain part of the difference between the pro-environment attitude means. There are more Hispanic Millennials in the weighted dataset relative to Hispanic Gen Xers, and considering that the models indicate Hispanics as being more pro-environment, a lower share of this ethnicity in Gen Xers is contributing negatively to the overall difference. Similarly, Republicans, who are less inclined toward a pro-environment attitude, constitute a higher share among Gen Xers, therefore contributing negatively to the overall difference.

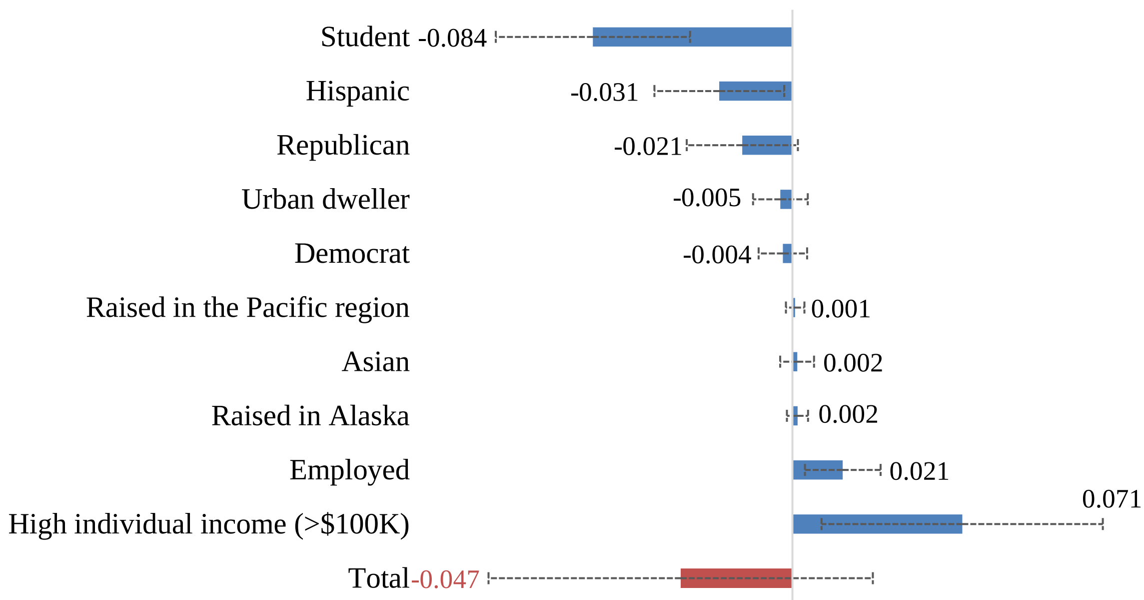


Figure 9 Contributions to the *endowment* portion of the difference in mean "pro-environment" attitude. *(Horizontal dashed lines refer to the 95% confidence interval)*

Now turning our attention to the contribution of life-stage variables, i.e. being a student, being employed, and having high individual income, we see that these variables contribute the most to the overall gap, although their opposing directions cancel out the overall effect. In other words, if Millennials were to "grow" into the shares of Gen Xers for these variables, their attitudes toward environmentally conscious living would roughly stay the same. We again caution that such predictions assume the temporal invariance of model coefficients.

2.8.4.2 Coefficient

The portion of the gap due to the difference in coefficients between the two generations is illustrated in Figure 10. Employment status and high individual income levels influence the two generations differently (see regression results in Appendix A.1), with Millennials who are employed or have high incomes showing a more environmentally friendly attitude relative to Gen Xers with the same characteristics. These differences, in other words, indicate that were the Millennials to have the same model coefficients as Gen Xers on these two variables, their average score on the pro-environment attitude would decrease by 0.224 (excluding the impact of other coefficient differences). Other non-life-stage variables whose (statistically meaningful) coefficient effects on the pro-environment construct differ between generations include belonging to the Asian race, and having a childhood residential location in the Pacific region. Gen Xers with these two characteristics tend to be more pro-environment than Millennials with the same characteristics, hence the positive change shown in Figure 10.

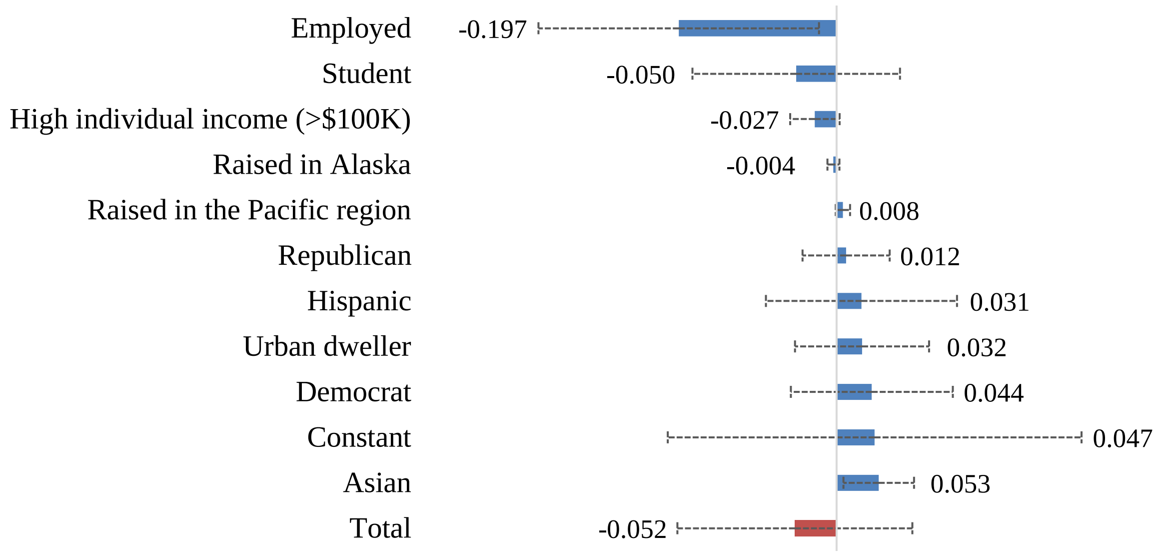


Figure 10 Contributions to the *coefficient* portion of the difference in mean "pro-environment" attitude. *(Horizontal dashed lines refer to the 95% confidence interval)*

2.8.4.3 <u>Interaction</u>

With respect to the interaction term, the life-stage variables have the largest contributions (although at lower significance levels). Based on Table 8, the incremental effects (on top of the all-else equal terms) of the simultaneous change of endowments/ coefficients for having a high individual income and being employed are -0.062 and -0.017, respectively. These two amplify the corresponding coefficient effects, and partly counteract the corresponding endowment effects. The total contributions of employment status considering all its components amounts to -0.193 s.d., the largest contribution of all variables, while the total contribution of high-income status here equals a relatively low -0.018 s.d., largely due to the opposite sign contribution of its interaction term compared to its endowment. With respect to the other life-stage variable, student, the interaction term contributes in the opposite direction to its endowment and coefficient terms, resulting in an overall contribution of -0.096 s.d. to the gap (second largest after employment status).

2.9 Conclusion

This analysis utilized data from a research survey executed in California to investigate generational differences in transportation-related attitudes, namely toward urban living (distinguishing between currently and long term), car ownership, and environmentally-conscious lifestyles. One simple but important result is that on average, those differences are small (0.15 – 0.20 standard deviation units) – albeit statistically significant – suggesting that generational distinctions are not as dramatic as they have been portrayed to be by popular media. Nevertheless, it is of interest to explore the sources of the differences that do appear – and, separately from the substantive content of the results in this study, to demonstrate a flexible methodology for comparing two groups that has numerous potential applications in transportation beyond the present one.

We linearly decomposed the differences in mean attitudes between Millennials and Generation X, and examined the decomposition terms which may be more likely to change as Millennials move into later life stages. The analysis shows that life-stage-related endowment disparities, such as in employment status, student status, income level, and marital status, explain significant portions of the overall attitudinal gaps. Our analysis also shows differential generational influences (coefficients) of these life-stage variables on attitudinal differences. We discussed interaction effects in greater depth and demonstrated the importance of considering such effects, highlighting the roles of the endowment and coefficient effects in concert with interactions.

In general, we can expect that the share of Millennials with life-stage characteristics such as being married will increase over time, i.e. that their endowment will approach that of Gen Xers (although, importantly, it may never reach Gen Xers', which has profound implications in a number of ways). It is much less clear how much the effect of such life-stage variables on an attitude will come to resemble that of Gen Xers' as Millennials continue to age. Effect magnitudes (coefficients), after all, are often functions of attitudes, lifestyles, and values – and so we can imagine an infinite regress, in which we need to know how much certain attitudes will change in order to fully understand how much others will change.

With respect to the pro-environment attitudinal construct, we see that Millennials tend to be more environmentally conscious, and it is unlikely that convergence of their life-stage variable shares to those of the Gen Xers will significantly impact this tendency – although convergence of the coefficients of those variables would. On the other hand, changes in life-stage variables may decrease the stronger tendencies of the younger generation toward urban living in the present time frame. With respect to long-term pro-urban tendencies, the generational differences appear less clear. Although there is not a statistically meaningful difference between Millennials and Gen Xers in long-term pro-urban attitudes, the difference becomes meaningful when we compare younger Millennials (< 26 years old) to older Millennials combined with Gen Xers. The greater tendency of younger Millennials toward long-term urban living may be reversed as they get married and start to have children. Similarly, the pro-car ownership attitude among Millennials, currently lower than for Gen Xers, would diminish the gap by 32% if the younger generation were married and had college degrees to the same extent as their older counterparts.

This study represents one of the first examinations of the influence of life stage variables on Millennials' transportation-related attitudes, and complements existing literature findings that Millennials' behaviors may be converging to those of Generation X as they enter later life stages. As such, the results of the current study pave the way toward better understanding if, why, and how travel-related behaviors or choices differ between generations. Such studies have important implications for transportation planning and forecasting, and further examination of differences in behaviors and attitudes across generational divides using longitudinally-designed studies should be a priority for transportation researchers moving forward.

CHAPTER 3. MODAL IMPACTS OF CALIFORNIA RIDEHAILING: A LATENT CLASS ANALYSIS WITH SHARED RIDEHAILING DISTAL OUTCOME

3.1 Abstract

This study investigates the latent patterns in the modal impacts of ridehailing services in a sample of California ridehailers, and how shared ridehailing adoption and usage (in addition to their determinants) are associated with these ridehailing modal impact patterns. Using a dataset collected in Fall 2018, we use a latent class with distal outcome approach to firstly identify the latent classes of ridehailing modal impacts, and then analyze the relationship between the identified latent classes and *shared* ridehailing adoption and usage while controlling for other factors that directly influence the adoption and usage. Our analysis points to three latent classes of ridehailing modal impact. In our first class, where ridehailers are younger, lower income, and more urbanite, a majority/plurality report a decline in the usage of taxi cabs and transit services. In our second and third classes, where ridehailers are relatively older and higher income, a majority of ridehailers report no change in their use of other modes, with the difference that Class 3 ridehailers also report being users of transit (as opposed to Class 2, who are not), but ridehailing usage does not impact their transit usage. Analyzing the association between these latent classes and shared ridehailing adoption and usage, we find Class 1 to have the highest adoption rate and usage frequency of shared ridehailing. Moreover, we conclude that 30% of the total shared ridehailing adopters, and 50% of the frequent users (weekly users), in our sample

are associated with Class 1 of ridehailing modal impact. This analysis helps provide a more detailed picture of how ridehailing interacts with other transportation modes in different population segments, and further investigates the sustainability promise of shared ridehailing by identifying its association with different modal impacts.

3.2 Introduction

Uber and Lyft, as the main representatives of the gig and platform economy in the U.S. transportation sector, have revolutionized the daily mobility of many travelers, with their array of services ranging from private and shared on-demand rides to bicycle/scooter sharing and food delivery. These services have consequently disrupted and challenged some longstanding transportation models and policies, a research subject of great interest to numerous studies that have aimed to unravel these services' impacts on travel demand and their interactions with other mobility choices. A number of studies, for instance, have pointed to the negative relationship between ridehailing (RH) and vehicle ownership (Hampshire et al., 2017; Ward et al., 2019), while a number of others point to the opposite conclusion (Gong, Greenwood, & Song, 2017; Ward et al., 2021). Several other studies have investigated the interaction of such services with public transit, with some pointing to circumstances where a complementary effect exists (e.g. Feigon & Murphy, 2016), while others discuss circumstances with negative impacts (Graehler Jr, Mucci, & Erhardt, 2018) – results which have fed into a growing concern for sustainable mass mobility options being downgraded or eliminated in the future. Such apparent divergence in conclusions and results may partly arise from heterogeneity in the ridehailing relationship with other elements of travel behavior, therefore calling for further research that better incorporates heterogeneity into the analysis.

Furthermore, and in light of the importance of ridehailing impacts on the transportation sector, many studies have aimed to better understand the growing market for these services, with several of them trying to identify the factors influencing these services' adoption and usage. As a result, literature often reports age, income, education level, land use, and personal attitudes as significant correlates of adoption and usage (Alemi et al., 2018). Most such studies, however, have focused on ridehailing services in general, not differentiating among the different services offered by the transportation network companies (TNCs). One such service, shared ridehailing, has significantly grown in availability and adoption since its limited introduction (in the United States) in late 2014. Considering that such shared rides are often considered and proposed as a more sustainable alternative to private rides or driving alone, a better understanding of the driving factors behind their usage and their impact on other modes can help modelers and planners better incorporate them in their analyses and understand their usage.

The main goal of this chapter, therefore, is to investigate the heterogeneity in the impact of ridehailing services on other travel modes, and how the adoption and use of *shared* RH and its determinants are related to the different modal impact patterns of ridehailing . To achieve this goal, we use a travel survey dataset collected in California in Fall 2018, and employ a latent class (LC) with distal outcome modeling framework in our analysis. Using this approach, we firstly identify the patterns of modal impacts of *any* ridehailing usage among different segments (latent classes) of the population, and then examine the relationship between *shared* ridehailing adoption and usage (as the distal outcomes) and the identified latent patterns. We will, therefore, also be able to partially assess the sustainability promise of shared ridehailing services through examining for which segments of the population these services tend to replace the less sustainable modes of transportation such as personal car.

The remainder of this chapter is structured as follows. In the next section, we provide an overview of the literature in this area, and what other studies report on the adoption and impacts of ridehailing services. In Section 3.4, we introduce our dataset in greater detail and provide an overview of our methodology. Section 3.5 discusses the heterogeneity (latent profiles) of the modal impacts of ridehailing services, followed by Section 3.6 where we discuss how shared ridehailing adoption and usage (and their determinants) are related to the identified latent profiles of modal impacts. We further discuss these findings in Section 3.7, and then close the chapter with concluding remarks in Section 3.8.

3.3 Literature review

Over the past several years, the concept of the sharing and platform economy, propelled by recent leaps in information and communications technology (ICT), has gained a strong foothold in the global market and has grown significantly in popularity among various segments of the population (Hamari, Sjöklint, & Ukkonen, 2016; Jin, Kong, Wu, & Sui, 2018; Kenney & Zysman, 2016; Zervas, Proserpio, & Byers, 2017). The appeal of such business models, owing largely to their convenience of use and lower costs (Nadler, 2014), has also impacted the transportation sector, with companies such as Uber and Lyft having changed the usual balance in the sector. Such businesses operate on the premise of providing on-demand rides by connecting willing suppliers (drivers) to consumers (passengers) all through an easy-to-access digital platform (e.g. smartphone app). To better cater to different needs and segments of the population, the ridehailing companies (also known as transportation network companies) have also diversified their services, not only providing economy and premium private rides, but shared rides as well. The adoption of these services has been a topic of interest in the literature over the past few years.

Rayle et al. (2016), using evidence from intercept surveys collected in the city of San Francisco, reported the appeal of such on-demand ride services to be stronger among younger, well-educated individuals, who like to avoid the longer wait times and inconveniences of driving and finding parking in the city. Alemi et al. (2018) investigated the adoption of ridehailing services over a larger area (state of California), estimating adoption models for ridehailing and finding that higher-educated older millennials tend to be among the more frequent adopters of these on-demand ride services, with living in a more mixed land-use area and having more long-distance travel further propelling this adoption. Clewlow and Mishra (2017) obtained similar findings on a more diverse scale (seven major US cities), reporting the rate of adoption among college-educated, affluent Americans to be twice that of the rest, and those living in urban neighborhoods to be significantly more likely to adopt. Young and Farber (2019) investigated ridehailing usage in the City of Toronto using a large-sample household travel survey, and concluded ridehailing to be a “wealthy younger generation phenomenon”. In general, most studies point to Millennials or the younger generation as the demographic with a higher adoption rate of ridehailing services.

In addition to studies on the adoption of ridehailing services, another body of literature has investigated the impacts of such services on other travel modes and urban conditions. Such impacts seem to differ based on the type of services, local context, and users' characteristics (Circella & Alemi, 2018). Hall, Palsson, & Price (2018), for instance, studied the impact of Uber on public transit using a difference-in-difference design, with results pointing to Uber acting as a complement for the average transit agency, although they comment that their reported average effects do not necessarily portray the existing heterogeneity well. A number of other studies have used the 2017 U.S. National Household Travel Survey (NHTS) to investigate the modal impacts of ridehailing services and point to a positive relationship between RH and public transit usage (Conway, Salon, & King, 2018; Grahn et al., 2019), although causality inference from such analyses is not possible. On the other hand, de Souza Silva et al. (2018), studying ridehailing in Brazilian cities, and Tang et al. (2020), studying the same topic in China, concluded that the majority of ridehailing trips replace those otherwise taken by taxis and public transit.

Considering the extent of studies on different aspects of ridehailing in general, the literature contains fewer studies that more specifically focus on shared ridehailing . Among the latter, Krueger et al. (2016) used an SP survey to explore the adoption of shared *autonomous* vehicles (SAVs), concluding that travel cost, travel time, and waiting times may play a critical role in the adoption of SAVs, and that younger and multimodal individuals are more likely to be among the adopters. In another study, Lavieri and Bhat

(2019) used both RP and SP data and developed a willingness-to-share concept to investigate individuals' willingness to share trips in an AV future. Their results point to a lower sensitivity to sharing commute trips with strangers compared to doing so on leisure trips, and indicate that the longer travel time of shared rides may be more of a barrier than exposure to strangers for the adoption of shared trips. Alonso-Gonzales et al. (2020) studied the different factors that influence an individual's decision to share rides using an SP dataset of Dutch urbanites. They report that willingness to share rides is clearly subject to population heterogeneity, and (similarly to Lavieri and Bhat) that a time-cost trade-off plays a more important role in shared ride usage than the potential disutility related to sharing space with strangers.

The importance of further studying shared ridehailing services lies in their promise of a more efficient and sustainable transportation system, where a higher vehicle occupancy, as some simulation studies show (Martinez & Viegas, 2017), may help relieve congestion and reduce the overall carbon footprint of the transportation industry. The sustainability promise of such services, however, hinges on the assumption that shared rides replace private rides, as opposed to public and active modes of transportation. Therefore, a more in-depth study of the interaction of shared ridehailing and other travel modes, in addition to the characteristics of its users, can help inform TNCs, planners, and policy makers.

In this study, we aim to extend the existing literature on the modal impact of ridehailing services by exploring the heterogeneity in the reported impacts of ridehailing on other travel modes, and how these different impact patterns relate to the adoption and use of shared ridehailing services and their determinants. This study will, therefore, contribute to the exisiting literature by shedding light on how shared ridehailing usage is associated with different RH modal impacts, and what user characteristics tend to bolster the adoption and usage of these services.

3.4 Overview of the dataset and methodology

3.4.1 Empirical context and study scope

As part of a multi-year research effort, the dataset used in this study was collected in Fall 2018 in the state of California. The survey was designed to extend and complement a similar effort carried out in 2015 within the same geography by the same team, aiming to add a longitudinal dimension to understanding the changing travel behavior and attitudes among the population (Circella, Matson, Alemi, & Handy, 2019). The data collection was accomplished through a mixed sampling method of stratified random sampling (mailing out a paper version of the survey to 30,000 randomly-selected households in the state), recruitment through online opinion panels, and reaching out to the same respondents who participated in the 2015 version of the study. The survey was designed to collect data on a wide range of travel-related topics, including personal attitudes and lifestyles; use of ICT and adoption of online social media; residential location and living arrangements; commuting and other travel patterns; auto ownership; awareness, adoption and frequency of use of several types of shared-mobility services; awareness of and opinions on autonomous vehicles; and sociodemographic traits. The final sample size of the dataset is approximately 3835 cases.

Since the goal of this study is to investigate the modal impacts of ridehailing and how they relate to shared ridehailing usage, we narrowed down the total sample to only ridehailing users, and ultimately worked with a sample of 1288 respondents. Moreover, and although the research team developed sample weights to better project the complete dataset onto the population at large, we decided against using any sample weights in the current study. The main reason behind this decision was that, as mentioned, the population of interest to the present study is that of ridehailers only. Since data on the distributions of various characteristics in the population *of ridehailers* is not available, we could not develop weights appropriate for this study. Accordingly, we conducted the analysis on the *unweighted* sample, while controlling for a number of sociodemographic characteristics in our model.

Table 9 Selected sociodemographic characteristics of the sample (N =1288)

Variable	Characteristics	N	Share
Gender	Female	631	49.0%
	Male	655	50.8%
	Transgender	2	0.2%
Age	18-37 years old	444	34.5%
	38-53 years old	441	34.2%
	54-72 years old	348	27.0%
	73-90 years old	55	4.3%
Race/ethnicity	White	986	76.6%
	Hispanic	174	13.5%
	Black	47	3.6%
	Other races	81	6.3%
Annual household income	< US $50K	251	19.5%
	US $50K- $100K	397	30.8%
	> US $100K	640	49.7%
Education	Bachelor's degree or higher	899	70.0%
	Some college/technical degree	293	22.7%
	High school diploma/lower	88	6.9%
Household (HH) size	Single-person HH	248	19.6%
	Two-person HH	472	36.7%
	Three-person HH	259	20.1%
	Four-person+ HH	301	23.4%
Employment	Workers (full/part time/two jobs)	972	75.5%
	Not a worker (unemployed/retired/homemaker/volunteer)	316	24.5%
Student	Full/part time student	174	13.5%

In addition to the socioeconomic and travel behavior variables, our dataset, as mentioned, also contains a rich array of attitudinal/perception statements. To most effectively leverage these variables in our analysis, we conducted a set of exploratory factor analyses (principal axis factoring with oblique rotation) to reduce the dimensionality and better capture the attitudinal and perception constructs behind those statements. We used the Bartlett method to generate the corresponding factor scores which were further used in our modeling. In the following subsection, we introduce the resulting constructs later used in our analysis.

3.4.2 Exploratory factor analysis (EFA) results

The survey included 30 attitudinal and lifestyle statements related to travel behavior. We extracted 9 attitudinal constructs with the EFA approach. The first section in Table 10 introduces three of the resulting constructs used further in our analysis. The pro-sustainability construct captures respondents' opinions toward stronger governmental or personal action to help the environment and remedy traffic congestion through better transit and fewer cars on the road. The pro-car construct captures the extent to which a respondent definitely wants to own a car and does not want to simply rent one as needed. Finally, the pro-suburban construct reflects opinions toward living in suburban neighborhoods, where houses tend to be bigger and mixed-use development and transit stops are not as prevalent as in urban areas.

We further conducted another EFA on a set of perceptions toward shared ridehailing. The second section of Table 10 details the resulting perception (toward mode attribute) constructs. The trip time construct captures the perception of respondents on the time-length attribute of shared ridehailing, and has perceptions regarding trip travel time, waiting time, reliability of trip time, and deviation from main route strongly loading on it. The trip safety and privacy construct captures respondents' perception regarding safety and privacy of shared rides, while the social interaction construct focuses on perceptions toward interaction among passengers.

Table 10 Summary of exploratory factor analysis (EFA) results of travel attitudes, perception, and behavior

Statement	Pattern Matrix Loading	Statement	Pattern Matrix Loading
	Attitudinal and lifestyle constructs[*,1]		
Pro-sustainability		*Pro car*	
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.93	I definitely want to own a car.	0.78
We should raise the price of gasoline to provide funding for better public transportation.	0.86	I am fine with not owning a car, as long as I can use/rent one any time I need it.	-0.44
The government should put restrictions on car travel in order to reduce congestion.	0.43	I prefer to be a driver rather than a passenger.	0.35
Pro-suburban			
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.	0.82		
I prefer to live close to transit even if it means I'll have a smaller home and live in a more crowded area.	-0.43		
I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	-0.29		
	Mode attribute perceptions[*,2]		
Social interaction		*Trip time*	
Interaction with strangers	0.73	Unreliable travel time	0.83
Sitting next to a stranger	0.72	Longer waiting time	0.80
Trip privacy and safety		Longer travel time	0.77
Safety	0.81	Deviation from main route	0.65
Privacy	0.77		

[*] The highest correlations between pairs of factor scores within each category are -0.18 and 0.25, respectively.
[1] Responses are on a five-level Likert-type scale (strongly disagree to strongly agree).
[2] Responses are on a five-level ordinal scale (strongly limiting to strongly encouraging).

3.4.3 Overview of the methodology

In this study, as mentioned, we use an LC model with distal outcome to achieve two goals. The first goal, namely investigating the heterogeneity in the impact of ridehailing on other modes, is accomplished through an LC cluster model whose indicators are the reported impacts of ridehailing as discussed in Section 3.5. This portion of the analysis, illustrated in Figure 11, is performed on all the ridehailers of the sample (N=1288). The latent clusters obtained as a result of this step show the heterogeneous modal impacts of ridehailing among different latent subsample groups. This methodology and the results of this portion of the analysis are further discussed in Section 3.6.

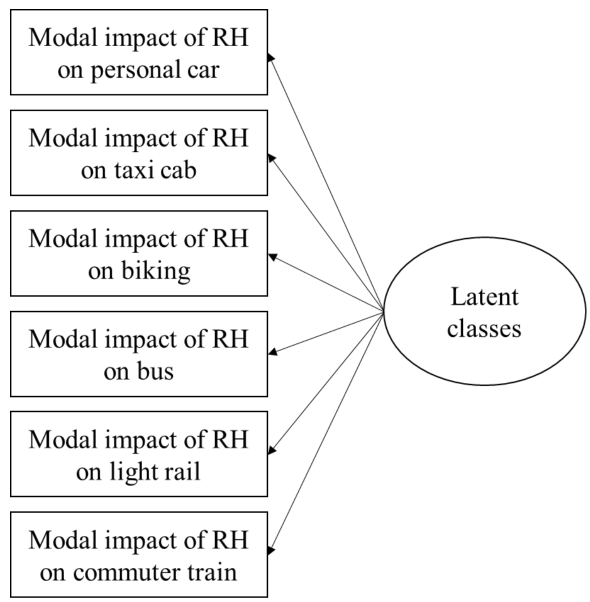


Figure 11 Schematic of the latent-class cluster analysis of this study

In the next step of this analysis, to address the second goal of the study we investigate how the adoption and usage of *shared* ridehailing services – in addition to their determinants – are associated with the identified latent classes. For this portion of the analysis, we only work with the subsample of ridehailers who we could reasonably claim had access to shared ridehailing services, and who also reported they were familiar with such an option (N=496). The methodology used for this step is a bias-adjusted LC model with distal outcome, through which shared ridehailing usage is analyzed in conjunction with the identified latent clusters of the previous step. The use of this method stands in contrast to using a one-step LC regression/choice model, where the membership and outcome model are simultaneously estimated. In the following, we present the reasons we chose the LC with distal outcome framework as opposed to the LC regression/choice model.

Although, in general, a one-step estimation of LC regression/choice models would result in efficient model parameters, it might not always be the preferred approach, for mainly two reasons. Firstly, in a one-step LC model, the dependent variable of interest (shared ridehailing adoption/usage here) influences the class formation, whereas it is conceivable that one would like to form the latent classes without such an influence, because they are of interest in their own right, separately from the dependent variable to be considered later (hence, "distal"). In such a case, it is preferable to form the latent classes first, and then analyze the relationship between the latent classes and the distal outcome in a later step. In our context, we are investigating the modal impacts of ridehailing services and how these impacts differ by sociodemographics and lifestyle segments; the latent clusters of those impacts are of interest for *all* ridehailers. The next, but separate, question of interest to this study is how these different modal impact patterns are related to using *shared* ridehailing services. A multi-step approach, therefore, allows us to accomplish both goals without confounding the first step with the influence of our distal outcome. Secondly, and from a theoretical point of view, it would not be justified to assume a causal relationship in either direction between the modal impacts of ridehailing and the adoption/usage of shared ridehailing. A more theoretically-sound model, in our context, would establish a correlation between these variables, assuming that there is a shared *latent* or *unobserved* trait that influences both, and through which the bivariate correlations are established. The causal diagram underlying our model here, as shown in Figure 12, employs such a logic, allowing the correlation to form through the categorical latent variable (latent classes). We present a more detailed discussion of the LC with distal outcome model in Section 3.6.2.

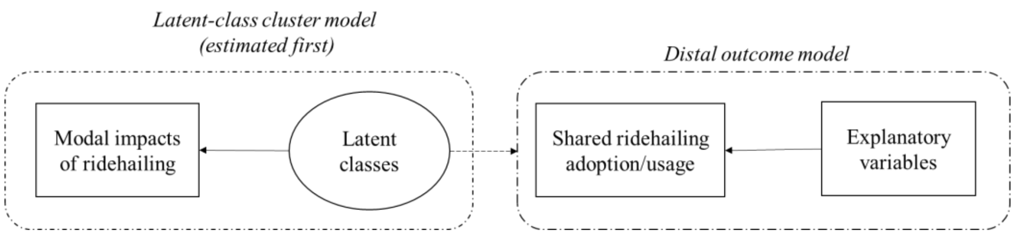


Figure 12 Schematic of the latent class with distal outcome model of this study

3.5 Investigating the heterogeneity of the modal impacts of ridehailing usage

3.5.1 Reported impacts of ridehailing on personal use of other travel modes

Asking respondents how using ridehailing services in general has impacted their use of other travel modes, the survey recorded their responses on a five-level ordinal scale from *much less* to *much more* for each of six other modes. In addition to these five levels, respondents could also report if they "did not use [a mode] before, and do not use it now", or if "[they] have changed how [they] use [a travel mode] but not *because of* ridehailing". To obtain a simpler and easily usable set of categories, in addition to having enough responses for each level, we recoded this variable into four categories by merging some of the options. In the final recoded variable (used in categorical format), 1 indicates that ridehailing has resulted in using the given mode much less or less; 2 indicates that ridehailing has *not* resulted in a change in the use of the mode (no change or no change due to ridehailing use); 3 indicates that ridehailing has resulted in an increased use of the mode (more and much more); and 4 indicates that a respondent did not use the mode in the past and present (not a user). Figure 13 shows the distribution of these categories in our sample.

As demonstrated in Figure 13, ridehailing services, as expected, have had the strongest negative impact on taxi cabs, with about 39% of ridehailing users in our sample reporting a lower use of this mode. Approximately 22% report that their use of taxi cabs has not changed due to ridehailing usage, and the share of those reporting that they use taxis more often as a result of using ridehailing services is the smallest at about 1.3%. Such respondents perhaps have used taxi cabs instead of ridehailing as a result of longer travel times, surge pricing, etc. for specific trips. Their low share, however, points to the relative scarcity of such instances.

Approximately 22% of ridehailing users in our sample report a lower use of personal car, while a majority of 66% report no ridehailing impact on their personal car usage. In addition, 3% of the sample report a higher use of this mode due to ridehailing services. This can possibly be either due to a complementary use of ridehailing services, where travelers use ridehailing for part of the trip where parking, for instance, might be more difficult to find, or cases where respondents get a ride from a family member for one leg of a trip and use ridehailing for the return trip. Similar to the taxis' case, their low share points to the relative scarcity of these cases.

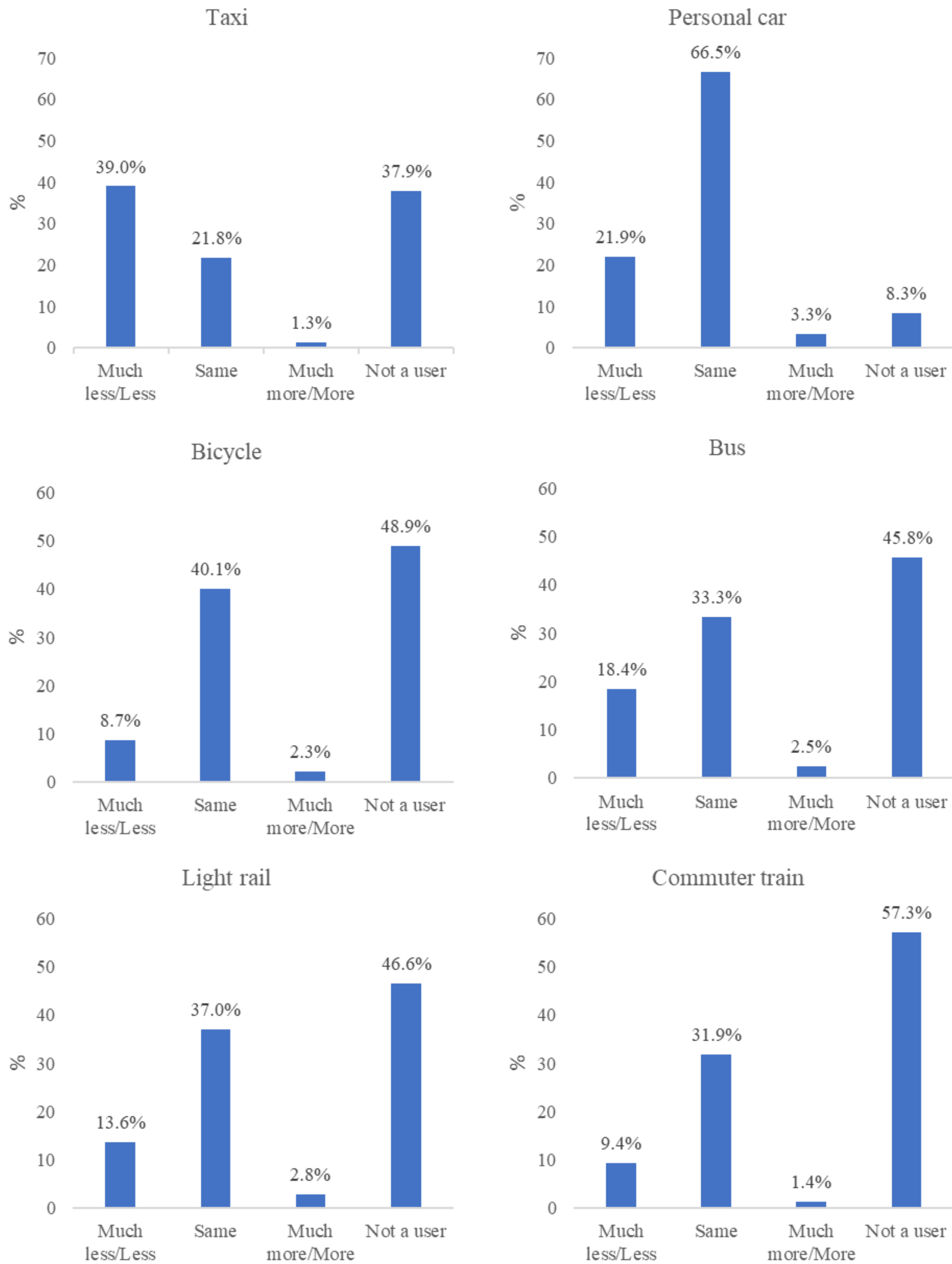


Figure 13 Distribution of the impacts of ridehailing services on traditional travel modes (N=1268)

Bicycling, as an active mode of travel, appears to have had the smallest impact from ridehailing services compared to the other modes, with only 11% of the sample reporting a different usage frequency (either increased or decreased). With respect to public transportation, the negative impact of ridehailing on these modes (bus, light rail/subway, commuter train) in our sample is the strongest for bus, with approximately 18% reporting a lower usage (34% of those who use bus), while this share is comparatively smaller at 14% and 9% (25% and 22%) for light rail and commuter rail modes, respectively. This observation, perhaps, draws attention to bus as the most afflicted transit mode, specifically considering how ridehailing can provide a faster and more convenient alternative to its user group, while light rail and commuter train seem to have been impacted relatively less. Moreover, the share of those reporting a higher transit usage, at around 1-3%, is quite small, indicating that the substitution impact of ridehailing services far outweighs their complementary effect on transit modes in our sample.

3.5.2 Methodology: Latent-class cluster analysis

We use the latent-class cluster analysis framework to capture heterogeneity in the impact of ridehailing services, and uncover the patterns of ridehailing modal impacts among different sociodemographic groups. LC cluster analysis consists of modeling a set of response variables or indicators (which can be on a categorical, ordinal, or continuous scale) using a categorical latent variable (indicating the distinct latent clusters) whose formation may also be influenced by a set of covariates (on a categorical or continuous scale). Given an LC cluster modeling framework, Eq. (10) defines the most general form of the probability density function $p(.)$ for an indicator vector y for an individual i given a covariate vector z that involves a latent categorical variable c to probabilistically classify the cases:

$$p(y_i|z_i) = \sum_{c=1}^{K} p(y_i|c, z_i)p(c|z_i)^5. \tag{10}$$

In Eq. (10), K is the total number of latent clusters. The conditional probability distribution for the latent categorical variable, or $p(c|z_i)$, is assumed to follow a multinomial logistic distribution, while the conditional probability distribution of the indicators is dependent on their type (assumed to be the normal distribution for continuous indicators, or multinomial/ordinal logit for categorical/ordinal indicators).

A number of assumptions are generally imposed on Eq. (10) to make it more parsimonious and computationally efficient. The first assumption involves the conditional independence of the model indicators y and covariates z given the latent class membership c. Implementing this assumption in Eq. (10) results in a simpler formula for latent class models:

$$p(y_i|z_i) = \sum_{c=1}^{K} p(y_i|c)p(c|z_i). \tag{11}$$

---

[5] Proof:

$$p(y|z) = \sum_c p(y, c|z) = \sum_c \frac{p(y,c,z)}{p(z)} = \sum_c \frac{p(y|c,z)p(c,z)}{p(z)} = \sum_c p(y|c, z)p(c|z).$$

Another common assumption imposed on latent class cluster models is the mutual independence of the model indicators given the latent class membership. Considering this assumption, we may rewrite Eq. (11) as:

$$p(y_i|z_i) = \sum_{c=1}^{K} p(c|z_i) \prod_{t=1}^{T} p(y_{it}|c), \tag{12}$$

where t indexes the model indicators y, with T being the total number of model indicators (T = 6, in our study, for the six modes shown in Figure 13).

These assumptions, however, are not always met in practice for all model variables, and investigating the model's bivariate residuals (BVRs) is a common approach to detecting violations of these assumptions (Vermunt & Magidson, 2013). If such violations exist, Eq. (12) can be modified to the correct probability structure, relaxing the conditional independence assumption (also known as local independence assumption) for the violating variables.

Within the context of our study, we used the ridehailing modal impacts introduced in the previous section as the latent class indicators (y). We decided, however, not to include any covariates (z) here for two main reasons. Firstly, the introduction of many covariates (sociodemographics, built environment, and other travel behaviors) either changed the distribution of the classes (and their characteristics) very little, implying that the indicators have a much stronger influence on class formation than the covariates in our analysis, or introduced model convergence issues. From a model parsimony and practical point of view, therefore, we decided that adding more model parameters may not be justifiable or possible. Secondly, considering the methodological approach of this study, it was prudent to save as many explanatory variables as possible for the distal outcome model in order for them to be used in directly modeling the adoption/usage frequency of shared ridehailing. Including them also as latent class covariates would have rendered the overall interpretation more convoluted. In other words, and according to Figure 12, the (rectangular) set of explanatory variables would have simultaneously influenced both the distal outcomes (shared ridehailing adoption/usage) *and* the latent classes. This, in turn, would have resulted not only in a direct influence of that set of variables on the distal outcomes, but also in a mediating influence through the LCs. The addition of a mediating influence could either render the direct influence on the distal outcome statistically insignificant, a result which was behaviorally less interpretable or desirable, or possibly make interpreting the direct and mediating influences together rather challenging. We, therefore, decided to keep the set of explanatory variables only for the distal outcome model portion of the analysis. Accordingly, Eq. (12) in our context would be:

$$p(y_i) = \sum_{c=1}^{K} p(c) \prod_{t=1}^{T} p(y_{it}|c), \tag{13}$$

and,

$$p(y_{it} = m|c) = \frac{e^{\beta_{tm}^{c}}}{\sum_{m'=1}^{M} e^{\beta_{tm'}^{c}}}, \tag{14}$$

where *m* indexes the categorical values that y_t can take on (less, same, more, and not a user, in our case), and *M* is the number of such values (four, in our case). For identifiability, we choose the restriction that $\sum_{m'=1}^{M} \beta_{tm'}^{c} = 0$ for all c, t. Note that without covariates, these probabilities are constant across *i*, meaning that individuals who have the same vector of indicators have the same probabilities. However, since – by construction – the latent classes will have different distributions of the indicators, they will also differ in their distributions of other variables, as shown in the following subsection.

3.5.3 Latent classes of ridehailing modal impacts

In choosing the optimal number of classes, we compared the log-likelihood (LL) statistics of different class numbers in addition to the interpretability of the results. Table 11 shows the different Information Criteria (IC) used to determine the optimal number of classes. The three-class solution has the minimum value for all the ICs (Bayesian IC (BIC), Akaike IC (AIC, AIC3), and Consistent AIC (CAIC)), suggesting that this model is an optimal solution with respect to the LL statistics.

Table 11 Summary of model estimation ICs by class number

Solution	LL	BIC	AIC	AIC3	CAIC	No. of parameters
1-Cluster	-7928.2	15985.0	15892.4	15910.4	16003.0	18
2-Cluster	-6904.3	14073.0	13882.6	13919.6	14110.0	37
3-Cluster	-6330.8	13383.3	12863.6	12964.6	13484.3	101
4-Cluster	-6355.7	13440.3	12915.5	13017.5	13542.3	102
5-Cluster	-6391.7	13455.0	12971.3	13065.3	13549.0	94

To better investigate the three-cluster solution, Figure 14 presents a summary of the three-cluster membership model results, while Table B.1 in Appendix B shows descriptive statistics for each cluster, as well as the parameters of the latent-class cluster model. As may be seen, the largest cluster (Class 2) includes 56% of the sample, with the rest of the sample roughly equally divided between the other two classes[6].

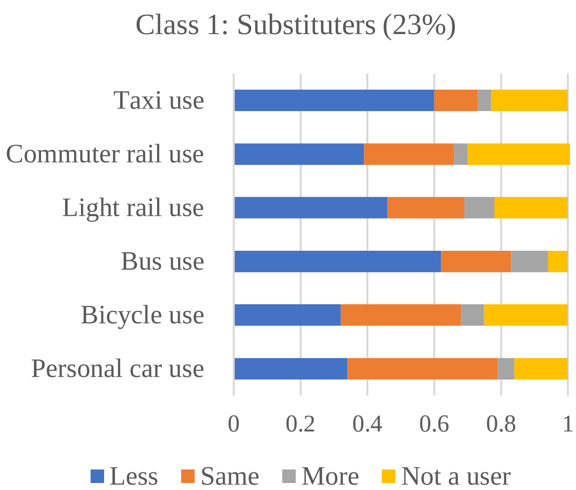
In Class 1, or the Substituters, ridehailing usage has the strongest negative impact on the use of public transit modes and taxi cabs, with a plurality or majority of the ridehailers in this class reporting a lower use of these modes. A sizeable portion of this class – especially when compared to the other classes – also reports a lower use of personal cars and bicycles, although these shares do not constitute a majority or plurality. For this latent class of ridehailers, therefore, ridehailing in general acts as a substitute mode, with this effect being more prominent for non-personal modes of transportation. With respect to the sociodemographic characteristics of this latent class of ridehailers, we see that they are on average the youngest (average age of 40 years old) of the three classes. In addition, the shares of lower incomes (those living in households earning less than $50K/year) and those living in households without a personal vehicle, at 47% and 25% respectively, are the highest for this class. In terms of education, we see a comparatively higher share of ridehailers with only a high school diploma or less (14%), and a lower share of ridehailers with bachelor's or higher degrees (59%). This class, in addition, contains a comparatively larger share of Hispanic ridehailers (27%), while the difference in the shares of other race groups is less pronounced. We also investigate each latent class with respect to attitudes

[6] We checked the BVRs for violations of the local independence assumptions, and found the direct correlations between the usage changes for bike and car, light rail and bus, commuter train and light rail, taxi cabs and personal cars, and taxi cabs and light rail to be large. We subsequently allowed direct correlations to exist between each violating pair of variables.

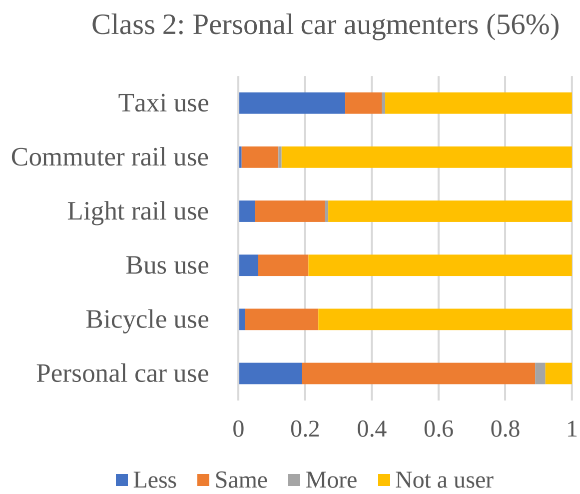
and lifestyles, since these traits have also been found to impact the use of ridehailing services. This class on average scores the lowest on the pro car and pro-suburban construct, indicating that ridehailers of this class, in line with some of their sociodemographic characteristics as discussed above, tend to have a more urban mindset and a lifestyle that favors or necessitates a lower rate of car ownership. In addition, members of this class have on average the strongest pro sustainability attitude.

Class 2, or the Personal car augmenters, is largely composed of those who are not users of non-personal or active modes of transportation. ridehailing in this class seemingly acts as a complement to the personal car for the majority of cases, while acting as a substitute for taxi and personal car in a comparatively smaller share of cases. Ridehailers in this class tend to be the oldest (with an average age of 48 years old) compared to the other two classes, and are also higher educated (with a 72% share of bachelor's degrees or higher) than ridehailers in Class 1. This class includes a lower share of low incomes (32%) than Class 1, with the share of those living in households without personal vehicles also considerably lower at 7%. With respect to attitudes, members of this class are on average the most pro car, as well as being the strongest pro suburban ridehailers. Moreover, the members of this class also have the lowest average score on the pro sustainability construct.

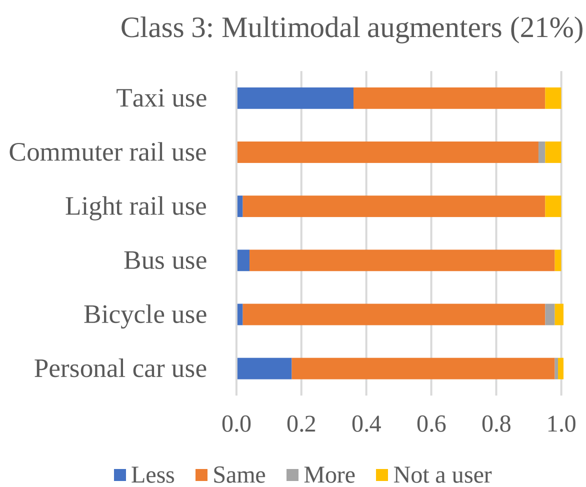
Finally in Class 3, or the Multimodal augmenters, a strong majority of ridehailers, unlike those in Class 2, are users of public transit and active modes of transportation. However, their use of ridehailing has not impacted (reduced or increased) their use of these modes, implying little to no substitution or bolstering effect of ridehailing on these modes for this class. Similar to Class 2, a majority of ridehailers in this class report that their use of personal car or taxi cabs has not changed due to ridehailing usage, although, again similarly to Class 2, a comparatively smaller share report a lower use of these two modes due to ridehailing usage. In terms of sociodemographics, ridehailers of this class are on average older (average age of 45 years old) than those in Class 1, but younger than those in Class 2. In addition, members of this class are somewhat higher educated than those in Class 2, with 78% having a bachelor's degree or higher. The share of higher and lower income households, at 53% and 30% respectively, points to this class as being slightly higher income than Class 1. In addition, the share of those living in households without personal vehicles is approximately similar to Class 2 at 6%. In terms of attitudes, this class scores, on average, between Classes 1 and 2 on car enthusiast, pro suburbia, and pro sustainability constructs.



SED: The youngest, lowest income, lowest education level, fewest vehicles owned, and with the highest share of living in urban areas
Attitudes: Most pro sustainable, least pro car and pro suburban



SED: The oldest, higher income and higher educated than Class 1, and with the lowest share of living in urban areas
Attitudes: Most pro car and pro suburban, least pro sustainable



SED: Average age between Classes 1 and 2, slightly higher income and higher educated than Class 2
Attitudes: In between Classes 1 and 2

Figure 14 Latent profiles of the modal impacts of ridehailing on other travel modes (x-axis shows the share in a class reporting a specific impact) (N=1268)

3.6 Shared ridehailing and its association with different ridehailing modal impact classes

As indicated in Section 3.4.3, it was relevant to identify modal impact latent classes for all ridehailers, and therefore the analysis in the previous section was performed on all such individuals, including those who lived in areas where shared ridehailing service was not available. Now, however, we wish to relate the modal impact classes to the usage of *shared* ridehailing, and therefore it becomes important to determine what portion of our overall sample could reasonably be said to have access to shared ridehailing services. To make this determination, we initially used the geocoded home addresses of the respondents in conjunction with the Uber API, and identified 1308 respondents (out of the total 3835) who lived where shared ridehailing services were available. An additional 208 respondents, whose home addresses did not fall within geographies where shared ridehailing services were available, indicated that they use shared ridehailing services. Considering that the majority of these cases used these services with low frequency (less than once a month), we believe they generally represent those who travel long-distance to areas where shared ridehailing is available. We decided against including these respondents in our analysis, since we could not reasonably include a counterpart group who did *not* use shared ridehailing given the same conditions, and doing otherwise could possibly bias our analysis. Moreover, we excluded cases who reported they were not familiar with shared ridehailing, since not being a user for them could not be considered as a *conscious choice.*

Based on this exploration, therefore, the restricted sample we used to conduct this portion of the analysis included those ridehailers who lived in areas where shared ridehailing was available and who were familiar with the option of shared ridehailing (N=496). We kept the same latent clusters as identified in Section 3.5.3, and checked to see if this sample restriction changed any of the class characteristics or overall patterns. All the classes kept their identified characteristics and patterns, with only negligible changes in average values. We also performed a separate LC cluster analysis only on the restricted sample and obtained similar results, further assuring that the sample restriction did not distort our identified latent clusters.

In the following subsections, we respectively present the distribution of shared ridehailing adoption and usage, explain the methodology employed to assess the relationship of these variables with the identified latent profiles of ridehailing modal impacts in the previous section, and report the results of this analysis.

3.6.1 Adoption and usage frequency of shared ridehailing services

Table 12 shows the descriptive statistics of shared ridehailing adoption and usage in our restricted sample. The shared ridehailing adopters constitute approximately 52% of the sample, with those who use this service on a regular basis (more frequently than “less than once a month”) forming about 29% of the total sample.

Table 12 Descriptive statistics of the adoption and usage of shared ridehailing among ridehailers having shared ridehailing available (N=496)

Variable	N	%
Shared ridehailing adoption		
Adopters	258	52.0%
Non-adopters	238	48.0%
Shared ridehailing usage frequency		
Not a user	238	48.0%
Less than once a month	115	23.2%
1-3 times a month	98	19.8%
1-2 times a week	34	6.9%
3 or more times a week	11	2.2%

3.6.2 Methodology: Latent class analysis with distal outcome

In an LC with distal outcome model (also known as three-step bias-adjusted LC model), we (1) estimate a standard LC cluster model where the parameters of the relationship between a latent class variable ($c = 1, .., K$) and model indicators (y) are identified; then (2) using the identified model parameters we predict the (posterior) probability of membership in each class for each case i with indicator pattern y_i ($p(c = k|y_i)$) and assign cases to the predicted classes according to their membership probabilities and an assignment rule; and (3) assess the relationship between the distal outcome variable of interest and the predicted classes. The two most popular assignment rules are modal assignment and proportional assignment. In modal assignment, a case is assigned fully to the class with the highest posterior class membership probability:

$$p(w = s|y_i) = \begin{cases} 1, & if\ p(c = s|y_i) > p(c = k|y_i)\ \forall s \neq k \\ 0, & otherwise, \end{cases} \tag{15}$$

where w denotes the *assigned* (predicted) class, in contrast to c, which denotes the *true* (albeit unknown) class. In proportional assignment, however, a case is assigned to a predicted class s with a *weight* of $p(w = s|y_i) = p(c = s|y_i)$ (which is the posterior class membership). The posterior class membership probability is computed as follows:

$$p(c = k|y_i) = \frac{p(y_i|c = k)p(c=k)}{p(y_i)} = \frac{p(y_i|c = k)p(c=k)}{\sum_k p(y_i|c = k)p(c=k)} = \frac{\prod_{t=1}^{T} p(y_{it}|c = k)p(c=k)}{\sum_k p \prod_{t=1}^{T} p(y_{it}|c = k)p(c=k)},$$

$$k = 1, 2, \ldots, K \,, \tag{16}$$

where the last equality holds given the same independence assumption as in Eq. (12), with T being the total number of indicators, and, as mentioned in Section 3.6.2, $p(c = k)$ is also assumed to follow a multinomial logistic distribution (in this case containing only constant terms).

As discussed in Bakk, Tekle, and Vermunt (2013), regardless of the assignment method, the true underlying classes (c) and predicted classes (w) will differ for some cases (although we will not know exactly for which ones). For instance, assume a sample of 100 cases in a two-class model where (for simplicity) the probabilities of belonging to Class 1 and Class 2 for all cases are equal to 0.7 and 0.3, respectively (meaning that the expected numbers of cases truly belonging to Classes 1 and 2 will be 70 and 30, respectively, although we do not know which 70 and which 30). In this example, if we use modal assignment, all cases will be assigned to Class 1, and we therefore will have an expected 30 cases that are misclassified as Class 1 while they truly belong to Class 2 (although we do not know which ones are misclassified). If we use proportional assignment, we can no longer speak of specific cases being assigned to specific predicted classes (since each case is “split” among classes in accordance with the associated posterior class membership probabilities); rather, we can only assess the expected number of cases in each predicted class, without knowing specifically which cases they are. In this instance, while the proportional assignment results in an expected 70 cases in Class 1 and 30 cases in Class 2 (in keeping with their true shares, unlike the case for modal assignment), there will still be a misclassification error. Each of the 70 expected cases in Class 1 has a 0.3 probability of belonging to Class 2 (yielding a misclassification of an expected $70 \times 0.3 = 21$ cases), and each of the 30 expected cases belonging to Class 2 has a 0.7 probability of belonging to Class 1 (yielding a misclassification of an expected $30 \times 0.7 = 21$ cases). Therefore, the total misclassification in this example would sum to 42 cases.

This misclassification is a consequence of the probabilistic nature of the latent classes and their separability. The more separable or deterministic the classes, i.e. the more different the class membership probabilities of the cases, the lower the misclassification error will be. This misclassification, as Bolck, Croon, and Hagenaars (2004) showed in detail, introduces an error into the assessment of the relationship between the identified latent classes and a distal outcome of interest, and we therefore need to adjust for the introduced error. Below, we discuss the procedure used to adjust for this misclassification bias.

We start with a representation of the causal diagram of a latent class model with distal outcome. This diagram is similar to that of Figure 12, but is reintroduced here with the associated mathematical notation and also adding the concept of the predicted class *w*, to better illustrate the intermediary step of this method. The distal outcome variable is denoted by d (shared ridehailing adoption/usage in our context), whose relationship with c we are interested in, and z denotes the external factors that directly influence the distal outcome. All other variables are as previously defined.

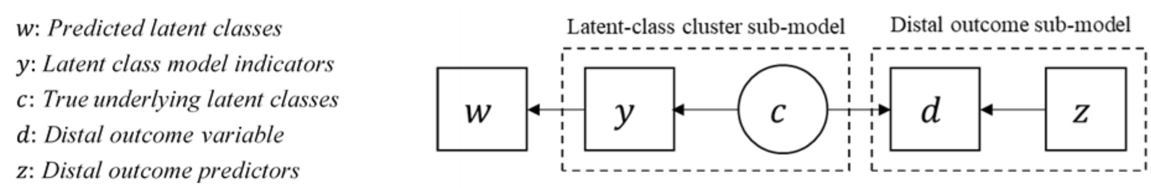


Figure 15 A general diagram of a latent class with distal outcome model

To estimate the correct relationship between d and c, we start from the joint probability of the predicted class (w) and the distal outcome (d), given a set of control variables (z) that directly influences the distal outcome, and introduce the true latent class variable (c) into the equation (Vermunt, 2010):

$$p(w = s, d_i|z_i) = \sum_k p(c = k)p(w = s, d_i|c = k, z_i). \quad (17)$$

Since the predicted class is conditionally independent from the distal variable given the true latent class (Figure 15), we have:

$$p(w = s, d_i|z_i) = \sum_k p(c = k)\, p(w = s|c = k)p(d_i|c = k, z_i). \quad (18)$$

In Eq. (18), $p(c)$ is the share of each latent class, and $p(w|c)$ indicates the misclassification (error) probability and is computed as follows[7]:

$$p(w = s|c = k) = \sum_i p(w = s|y_i)p(y_i|c = k)$$

$$= \sum_i p(w = s|y_i) \prod_{t=1}^{T} p(y_{it}|c = k). \qquad (19)$$

The first probability on the right-hand side of Eq. (19) is given by Eq. (15) or (16), and the second term appears in Eqs. (11) and (12) (with T denoting the total number of indicators), assuming a conditional independence between the indicators. Both may be computed from the first step of the latent class with distal outcome analysis, and therefore are fixed values (Bakk et al., 2013). The probability $p(d_i|c, z_i)$, in our context, is modeled using either a binary logit (in the case of adoption) or ordinal logit (in the case of usage

[7] Proof:

$$p(w|c) = \sum_y p(w, y|c) = \sum_y \frac{p(w,y,c)}{p(c)} = \sum_y \frac{p(w|y,c)p(y,c)}{p(c)} = \sum_y p(w|y, c)p(y|c).$$

Since w is directly determined only by y (w and c are independent given y), $p(w|c) = \sum_y p(w|y)p(y|c)$.

frequency) formulation, and the associated unknown parameters of the model are obtained by maximizing the log-likelihood function associated with Eq. (18)[8]:

$$LL = \sum_i \sum_s ln \sum_k p(c = k)\, p(w = s|c = k) p(d_i|c = k, z_i)\ . \tag{20}$$

3.6.3 Results

3.6.3.1 Shared ridehailing adoption

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[8] As Eq. (20) shows, the LL statistic of the estimated model would be associated with the joint probability distribution, rather than the univariate distribution of just the distal outcome. We can marginalize the joint probability over the predicted posterior class (w), obtaining the conditional distribution of the distal outcome. Specifically, summing Eq. (18) over s gives:

$$\sum_s p(w = s, d_i|z_i) = \sum_s \sum_k p(c = k)\, p(w = s|c = k) p(d_i|c = k, z_i)$$

$$= \sum_k p(c = k) p(d_i|c = k, z_i) \sum_s p(w = s|c = k) = \sum_k p(c = k) p(d_i|c = k, z_i) = p(d_i|z_i),$$

since $\sum_s p(w = s|c = k) = 1$. In this approach, the parameters of the $p(d_i|c = k, z_i)$ model are not directly estimated, since the LCs are modeled in an earlier stage, and c is not known for the latter model. However, once the estimated parameters of that model have been corrected by taking the misclassification error into account as shown in Eqs. (18) – (20), we can simply write the desired marginal likelihood as $\prod_i p(d_i|z_i)$, and the log-likelihood as:

$$\sum_i \ln p(d_i|z_i) = \sum_i \ln \sum_k p(c = k) p(d_i|c = k, z_i).$$

Table 13 shows the distribution of shared ridehailing adoption within and across the identified latent classes (as introduced in Section 3.5.3). Based on the within-class distribution statistics, we see that Class 1 has the highest rate of shared ridehailing adopters, with the other two classes having fairly similar adoption rates. But more importantly, by looking at the across-class distributions, we see that 30% of the shared ridehailing adopters in our sample belong to Class 1 (Substituters), where ridehailing largely impacts public transit and taxis. On the other hand, 49% of adopters in our sample belong to Class 2, the Personal car augmenters who largely do not use public or active modes of transportation, with another 21% belonging to Class 3, the Multimodal augmenters for whom ridehailing largely does not impact public transit usage. In other words, 70% of shared ridehailers in our sample are associated with ridehailing modal impact patterns where ridehailing appears to have minimal impact on active and public modes (more sustainable modes), while the remaining 30% are associated with the modal impact cluster where public transit's usage has been substantially weakened.

Table 13 Distribution of shared ridehailing adoption within and across the identified latent classes (N=496)

Descriptive statistics type	Class (share) / Adoption category	Class 1: Substituters (26%)	Class 2: Personal car augmenters (51%)	Class 3: Multimodal augmenters (23%)
Distribution *within* class (Average $p(d_i \mid c, z_i)$)	Non-adopters	0.40	0.49	0.51
	Adopters	0.60	0.51	0.49
Distribution *across* classes (Average $p(c \mid d_i, z_i)$)	Non-adopters	0.21	0.54	0.25
	Adopters	0.30	0.49	0.21

In addition to the association of shared ridehailing and identified latent classes, we further investigated other direct determinants of shared ridehailing and how they differ based on the identified latent classes. Table 14 shows the binary logit models of shared ridehailing adoption with the explanatory variables including sociodemographics, built environment, and attitudinal factors (statistically insignificant coefficients have been constrained to zero). Overall, we see that Class 2 is associated with the highest number of explanatory variables, likely due to its largest size and the existence of more heterogeneity than for the two smaller classes.

Table 14 Distal outcome model (binary logit) of shared ridehailing adoption (N=496)

Variables	Class 1: Substituters		Class 2: Personal car augmenters		Class 3: Multimodal augmenters	
	Coef.	P-value	Coef.	P-value	Coef.	P-value
Age (years)	-	-	-0.041	0.002	-	-
High income household (> $100K/yr)	-	-	-0.883	0.019	-1.517	0.002
Urban dweller	1.135	0.022	0.639	0.062	-	-
Frequency of long-distance leisure air travel[1]	-	-	0.111	0.043	0.218	0.069
Transit meets my needs[2]	0.039	0.047	-	-	0.357	0.042
FS[3] open to interaction with strangers	0.467	0.086	0.955	<0.001	-	-
FS pro sustainability	-	-	0.417	0.013	-	-
Constant	-1.048	0.094	1.695	0.010	-0.511	0.340

Distal outcome model statistics:
LL_{EL}=-343.80, LL_{MS}=-343.40, LL_{β}=-295.60
ρ_{EL}=0.140, ρ_{MS}=0.139

[1]Transformed to a continuous per month variable from the original ordinal variable using this logic: "5 or more times a week"= 5 times a week (20/month), "3-4 times a week"= three and a half times a week (14/month), ''1–2 times a week''=1.5 times a week (6/month), ''1–3 times a month'' = 2 times a month (2/month), "less than once a month" = 3 times per year (0.25/month), and "Never" = 0/month.
[2] Ordinal five-level Likert-type variable.
[3]Factor score generated based on the exploratory factor analysis using Bartlett method.

Among the sociodemographic variables, as Table 14 shows, we found age and household income to be significant predictors of shared ridehailing adoption. In our Class 2 (Personal car augmenters), age is negatively associated with shared ridehailing adoption, indicating that younger ridehailers in this class are more likely to be among the adopters. Although the coefficients of age in the other two (younger, on average) classes were also negative, we did not find them to be statistically significant, and therefore constrained those coefficients to zero. With respect to income, we see that ridehailers of Classes 2 and 3 who live in high-income households are less likely to be among the adopters, while the influence of income is insignificant in the Substituters Class, whose members already live in relatively lower income households.

The built environment is significantly correlated with shared ridehailing adoption in our first two classes, with those living in urban areas more likely to be among the adopters than suburbanites. This effect is more significant in Class 1, which has a larger share of younger ridehailers whose use of transit has been negatively impacted, while this variable's impact in the two Augmenter Classes is of lower statistical significance. Moreover, a higher frequency of long-distance leisure air travel is positively associated with using shared ridehailing in the two Augmenter Classes.

With respect to opinions and attitudes, we see that ridehailers in Classes 1 and 3 who indicate that public transit meets their needs are more likely to be among adopters, while this effect is insignificant in Class 2, where a majority of ridehailers are not users of public transit. In addition, we see that an openness to interaction with strangers on rides, as expected, is positively associated with shared ridehailing adoption in Classes 1 and 2.

This association is strong in our older car-centric users (Class 2), but considerably weaker in our younger classes whose other characteristics are more in line with using shared rides. Finally, pro sustainability ridehailers in Class 2, a class in which pro sustainability is on average the lowest, are more likely to adopt shared ridehailing.

3.6.3.2 Shared ridehailing usage frequency

Although it is important to understand what factors influence the adoption of shared ridehailing services, it is even more important to study the determinants of the usage frequency of these services, as that would provide us with more insight into the impact of shared ridehailing. As presented in Table 12, usage frequency of shared ridehailing in our dataset has 5 ordered levels; however, considering that the "3 or more times a week" usage level has a low number of cases, we merged it with the previous level, and named the new level the "frequent users". Subsequently, the monthly users are considered moderate users, those using this service "less than once a month" are considered infrequent users, and those not using shared ridehailing are considered "non-users". Following this definition, therefore, we consider this 4-level ordered usage frequency of shared ridehailing as the new distal outcome and use an ordered logit framework in conjunction with the identified latent classes. Table 15 shows the distribution of the usage frequency of shared ridehailing in and across the identified latent classes.

Table 15 Distribution of the shared ridehailing usage frequency within and across the identified latent classes (N=496)

Descriptive statistics type	Usage category \ Class (share)	Class 1: Substituters (26%)	Class 2: Personal car augmenters (51%)	Class 3: Multimodal augmenters (23%)
Distribution *within* class	Non-users	0.38	0.50	0.53
	Infrequent users	0.24	0.22	0.27
	Moderate users	0.23	0.21	0.16
	Frequent users	0.14	0.07	0.04
Distribution *across* classes	Non-users	0.21	0.53	0.25
	Infrequent users	0.27	0.46	0.27
	Moderate users	0.28	0.55	0.17
	Frequent users	0.50	0.41	0.09

As the within-class distribution part of Table 15 demonstrates, the Substituters Class (with younger, more urbanite ridehailers) has the highest shares of frequent and moderate shared ridehailing users. In addition, this class has the lowest share of non-users. Considering that the majority/plurality of ridehailers in this class report a lower use of transit services, we may confirm that: (1) the younger and lower income class of ridehailers is associated with a higher use of shared ridehailing services, and (2) a higher impact on transit usage is associated with a higher usage of shared ridehailing services. The within-class distribution of usage frequency in the Personal car augmenters Class is relatively higher than that of the Multimodal augmenter Class with the share of frequent users 3 percentage points, and the share of moderate users 5 percentage points, higher than those of the Multimodal augmenters. In both classes, moreover, the share of non-users is fairly similar, with approximately half the ridehailers in each class reporting not having used shared ridehailing services.

The across-class distribution of shared ridehailing usage shows that approximately 50% of the frequent, and 28% of the moderate, shared ridehailers in the total sample belong to the Substituters Class, with younger urbanite members. This result further confirms the uneven distribution of different usage frequencies, and how the class of ridehailers with a higher share of reported lower usage of transit is associated with a bigger share of frequent shared ridehailing users, results that cast doubt on the overall sustainability promise of shared ride services. We further conclude that 50% of the frequent, and 71% of the moderate, shared ridehailers in the total sample belong to the Augmenters Classes, where active and public modes of transportation are the least affected.

We now turn to the other direct determinants of shared ridehailing usage frequency and how they differ in each latent class of users. As shown in Table 16, age is a significant predictor of usage frequency in our oldest class of ridehailers (Class 2), indicating that the younger ridehailers within that class tend to use shared ridehailing more frequently. Similar to the result for adoption (Table 6), however, the age effect is not significant for the other two classes, who are relatively younger to start with. Car ownership and income status also influence usage frequency across the classes; those ridehailers in Class 1 who do not own (or lease) a car tend to use shared ridehailing more frequently. Among Class 2 and Class 3 ridehailers, moreover, those who live in higher income households tend to use shared ridehailing less often, a result in line with that of the adoption model.

Urban environment influences usage frequency only in Class 2 (as opposed to the adoption model where it also played a role in Class1), indicating that the ridehailers in this class who live in urban areas tend to use shared rides more frequently. This built environment effect is probably more pronounced in this class (as opposed to the other two classes) since it already comprises the smallest share of urban dwellers.

With respect to opinions toward using shared ridehailing, we see that, as expected, a higher tolerance toward longer travel times and interaction with strangers on shared rides is associated with a higher usage of shared ridehailing, although the former showed a statistically insignificant association with the adoption of these services. Specifically, Class 2 ridehailers who are more open to interaction with strangers on rides tend to use shared ridehailing more often, while ridehailers in Classes 1 and 3 who are less bothered by the longer travel times of shared rides are likely to use it more often. This result further underlines the importance of an openness toward the “sharing” economy in our oldest class, as opposed to the younger ones, in adopting and using these services. In addition, we see that those in Class 2 with a stronger pro-sustainability attitude tend to use shared rides more often, and ridehailers in Classes 1 and 3 who express that public transit meets their needs tend to use shared rides more often.

Finally, and similar to the adoption model, we see that those in the Augmenters Classes who take more leisure trips by air tend to use shared ridehailing more often, while this effect is insignificant for Class 1 ridehailers.

Table 16 Distal outcome model (ordered logit) of shared ridehailing usage frequency (N=496)

	Class 1: Substituters (26%)		Class 2: Personal car augmenters (51%)		Class 3: Multimodal augmenters (23%)	
	Coef.	P-value	Coef.	P-value	Coef.	P-value
Age (years)	-	-	-0.028	0.005	-	-
High income household (> $100K/yr)	-	-	-0.449	0.051	-0.631	0.022
Not a car owner	1.117	0.011	-	-	-	-
Urban dweller	-	-	0.710	<0.001	-	-
Transit meets my needs[1]	0.227	0.040	-	-	0.167	0.097
Frequency of long-distance leisure air travel[2]	-	-	0.0694	0.021	0.015	0.001
FS[3] open to interaction with strangers	-	-	0.336	<0.001	-	-
FS tolerant of longer trip time	0.246	0.044	-	-	0.260	0.070
FS pro sustainability	-	-	0.336	0.001	-	-
Constants						
Moderate user | frequent user	0	-	0.803	-	0	-
Infrequent user | moderate user	-0.966	0.012	0.3328	0.45	-0.6858	0.075
Non-user | infrequent user	-1.775	0.0015	0	0.32	-1.5289	0.014

Distal outcome model statistics:
LL_{EL}=-686.22, LL_{MS}=-609.03, LL_{β}=-533.33
ρ_{EL}=0.223, ρ_{MS}=0.124

[1] Ordinal Likert-type scale variable.
[2] Transformed to a continuous per month variable from the original ordinal variable using this logic: "5 or more times a week"= 5 times a week (20/month), "3-4 times a week"= three and a half times a week (14/month), ''1–2 times a week''=1.5 times a week (6/month), "1–3 times a month" = 2 times a month (2/month), "less than once a month" = 3 times per year (0.25/month), and "Never" = 0/month.
[3] Factor score generated based on the exploratory factor analysis using Bartlett method.

3.7 Discussion

The analyses in the previous sections highlight different aspects of ridehailing and their interaction with other travel modes. Based on the results of Section 3.5.1, and as expected, we see the taxi industry as the most strongly impacted mode due to ridehailing services, with all three of our latent classes in Section 3.5.3 also showing a substantial negative impact on the use of taxi cabs. Whether taxi cabs are a "greener" or more efficient mode of transportation is up for argument. While ridehailing services use advanced algorithms to minimize empty miles, and in the case of shared ridehailing match passengers on similar routes, taxi fleets in some areas like San Francisco have been converted to alternate fuel vehicles (SFMTA, 2014), hence reducing their impact on the environment and air quality.

The second most strongly hit mode due to ridehailing in our analysis is personal cars, with approximately a quarter of the sample reporting a lower use of this mode. A lower use of personal cars may be counted as a positive impact of ridehailing services, since it can help reduce some urban maladies such as unwarranted parking spaces in urban areas (Zhang, Guhathakurta, Fang, & Zhang, 2015). Such a benefit, however, may not positively materialize for other dimensions such as congestion and VMT, as multiple studies point out that ridehailing services appear to have an adverse effect on these measures (Erhardt et al., 2019; Henao & Marshall, 2019; Tirachini & Gomez-Lobo, 2020).

With respect to transit, our sample shows the negative impact of ridehailing to be considerably stronger than its positive impact. Although a small portion of our ridehailers reported a higher use of transit as a result of using ridehailing, their share is too small to even influence the formation of a distinct latent class where its members generally report a complementary effect of ridehailing on transit. In this respect, our analysis is more in line with previous work which points to a stronger ridehailing substitution effect on transit rather than a bolstering impact (de Souza Silva, de Andrade, & Alves Maia, 2018; Tang et al., 2020). In addition, active modes of transportation, represented by bicycling in our data, show to be the least impacted by ridehailing, with only 10% of the sample reporting a lower usage level, and perhaps point to the low competition between this mode and ridehailing, especially considering its smaller usage group and intended distance range.

Our latent classes of ridehailing modal impact further shed light on how ridehailing impact differs among various population segments. While taxi cabs, as mentioned, show a substantial share of usage decline in usage across all the three classes, in our younger, lower income, and more urbanite class of ridehailers it is transit that also shows a sizeable share of usage decline as a result of using ridehailing. In contrast, in the older and higher income classes of ridehailers we see a decline in personal car usage in addition to taxi cab usage while public and active modes of transportation do not see a noticeable impact. We, in addition, see signs of generational divide among the classes. Our younger class, who is earning less, exhibits a higher pro sustainable attitude, in addition to being less pro suburban and pro car, attitudinal patterns that an earlier analysis on a similar data set collected in 2015 has shown to be present in the younger generation (Etezady, Shaw, Mokhtarian, & Circella, 2020).

The adoption rate and usage of shared ridehailing, moreover, is also higher in the Substituters Class, which has younger and more urbanite ridehailers (Class 1). This observation agrees with other studies on sharing economy consumption (Winkle et al., 2018), with the younger generation often reported as avid partakers of the sharing economy. It is, however, important to notice that based on our analysis, the younger generation usage of shared ridehailing tends to also come at the expense of transit, which is still a more sustainable travel option. Especially, we see that the ridehailers in this class (and also in Class 3) who indicate that transit can meet their needs are more likely to be among the adopters of shared ridehailing, further underlining the competition between transit and shared ridehailing among ridehailers who are also users of transit.

We, moreover, see a strong influence of sociodemographics and built environment in the adoption and usage of shared ridehailing in all our classes. Lower age and income, fewer owned vehicles, and being an urbanite tend to be positively associated with shared ridehailing adoption or usage in one or all of the classes. We further see that a stronger attitude toward sustainability increases the likelihood of higher adoption or usage only in our older class of ridehailers. Although our younger classes are on average more pro-sustainable, we see insignificant evidence of the role of this attitude in the adoption and use of these services among those ridehailers.

One psychological impediment in the adoption and usage of shared ridehailing is sharing the vehicle space with another passenger. We see the effect of this factor (in the form of being open to interacting with strangers) strongly in our older car centric class (Personal car augmenters), while such an effect is considerably weaker in statistical significance among the younger classes. This observation, as mentioned, further underlines a generational divide with respect to the sharing economy, where the older generations tend to be more concerned about collaborative consumption, and this factor plays a more important role in their decision toward partaking in the sharing economy.

3.8 Conclusion

In this study, we focused on uncovering how ridehailing modal impacts differ across population segments, and how shared ridehailing usage frequency is associated with the identified modal impact patterns. To achieve these goals, we first estimated a latent class cluster model with self-reported ridehailing modal impacts used as the indicators of latent class. The resulting three classes showed distinctly different impacts: transit and taxis showed sizable shares of usage decline among the younger, lower income, and urbanite ridehailers, while higher income, older ridehailers tend to belong to classes where ridehailing is largely supplemental to their use of other modes, but when there *is* an impact, it tends to be a reduction in the usage of personal cars and taxi cabs.

To investigate the association of *shared* ridehailing and the identified latent classes, we used a latent class model with distal outcome approach, thereby analyzing a bias-adjusted joint association between the latent classes and our distal outcomes. We concluded that shared ridehailing adoption rate and usage frequency are higher in our Substituters Class, where transit and taxis see sizable shares of usage decline as a result of using ridehailing services. Moreover, 30% of the total number of shared ridehailing adopters in our sample and 50% of the frequent users (more than once a week) are associated with this class. On the other hand, 72% of the moderate users and 73% of the infrequent users are associated with the two (Augmenters) classes having a negligible impact on active and public modes of transportation. These results, as discussed, cast doubt on the overall sustainability of shared ride services, considering that the large share of frequent users associated with the Substituters Class.

Furthermore, we saw a strong influence of SED variables, in addition to attitudes and perceptions, on the adoption and usage of shared ridehailing. In general, we concluded that a younger age and lower income level are associated with a higher adoption and usage level of shared rides, while a stronger pro-sustainability attitude and an openness to interaction with strangers on rides more significantly influences the adoption and usage of shared ridehailing among the older more car centric ridehailers.

CHAPTER 4. ON THE INTERACTION OF RIDEHAILING USAGE FREQUENCY, VEHICLE AVAILABILITY, AND EXPECTATIONS TO CHANGE VEHICLE OWNERSHIP AMONG CALIFORNIANS: A LATENT-CLASS TRIVARIATE MODEL

4.1 Abstract

In this study, we propose a trivariate latent-class modeling framework to jointly study ridehailing usage frequency, vehicle ownership, and expectations to change vehicle ownership. We use a dataset (N=3141) based on a custom-designed travel survey administered in Fall 2018 in the state of California. The proposed model, in addition to accounting for parameter heterogeneity through outcome-variable-specific latent segmentations, allows for an insightful behavioral interpretation of the relationships among the variables that indicate membership in the latent segments associated with each outcome variable. Our results point to more nuanced relationships between the three variables of interest and the external factors associated with them than what most other studies in the literature have revealed so far. More specifically, we see a less straightforward relationship between age and ridehailing usage frequency, for which other studies have generally pointed to a negative relationship. Our results reveal two latent clusters of approximately similar average age who show drastically different ridehailing usage frequency. Furthermore, although we see evidence of a negative association between vehicle

availability and ridehailing usage frequency, our latent class framework again reveals two clusters with approximately similar vehicle availability but different ridehailing usage, pointing to the influence of other factors such as attitudes and the built environment in differentiating their ridehailing usage. With respect to the relationship between ridehailing usage and expectations to change vehicle ownership, our results show that, of the two clusters with similar vehicle availability and age, the one with higher ridehailing usage is less likely to expect an increase in household vehicle ownership within the next three years. This result shows some promise for the future impact of ridehailing services in containing increases in car ownership.

Keywords: vehicle ownership, ridehailing, ridesourcing, latent-class models, joint models, trivariate models

4.2 Introduction

Ridehailing (RH) services have been a growing topic of research in the transportation and economics literature over the past several years, with a large body of this literature motivated by a need to better understand the adoption and usage in addition to the mobility and economic impacts of these services. With respect to ridehailing adoption and usage, the literature often agrees that younger, higher educated, and urban travelers are more likely to adopt and use these services (Alemi, Circella, Handy, & Mokhtarian, 2018; Clewlow & Mishra, 2017; Rayle, Dai, Chan, Cervero, & Shaheen, 2016; Young & Farber, 2019), while consensus is yet to form over the mobility impacts of these services. Among the several mobility impacts of ridehailing services, the interaction of ridehailing and vehicle ownership (VO) has been a topic of growing interest among researchers and practitioners, with studies often drawing opposing conclusions on the nature of this relationship. While some studies have reinforced the initial claims that ridehailing services can decrease vehicle ownership rates among households (Hampshire, Simek, Fabusuyi, Di, & Chen, 2017; Sabouri, Brewer, & Ewing, 2020; Ward, Michalek, Azevedo, Samaras, & Ferreira, 2019), others have cautioned or pointed out the opposite (Gong, Greenwood, & Song, 2017; Ward et al., 2021). Although the direction of causality in the relationship between ridehailing usage and vehicle ownership levels may prove elusive or complex, it is important to model these two variables together so as to factor the joint nature of these decisions and the shared unobserved variability between them into the modeling process.

Evidence for the nature of the relationship between ridehailing usage and vehicle ownership levels may also coincide with that of generational differences in attitudes and choices, with early research showing that Millennials tends to have a lower rate of licensure, vehicle ownership, and vehicle miles traveled (Delbosc & Currie, 2013; Hopkins, 2016; Kuhnimhof et al., 2012). Similarly, the Millennial generation is reported to be strong consumers of the sharing economy (Anderson & Rainie, 2010; Ranzini et al., 2017), a trend that encourages lower ownership rates and higher consumption of shared resources, giving rise to the expectation that the sharing economy may have a disparate role in the vehicle ownership decisions of different generations.

The literature, moreover, is already showing evidence that such aforementioned trends may not be enduring, as several studies hint at the Millennial generation growing out of their unique trends of higher sharing economy consumption (Hudson, 2015; Rebell, 2015), and lower vehicle ownership rates and car dependence (Etezady, Shaw, Mokhtarian, & Circella, 2020; Lavieri, Garikapati, Bhat, & Pendyala, 2017). A question of further interest, therefore, is how expectations to change vehicle ownership levels interact with current vehicle ownership decisions and sharing economy consumption, and whether, and to what degree, such expectations are subject to heterogeneity in the population.

Accordingly, the main goal of this study is to jointly investigate the ridehailing usage frequency, vehicle ownership levels, and expectations to change vehicle ownership levels (within the next three years) while accounting for heterogeneity with respect to lifestyle and age. We argue that belonging to a certain generation alone does not determine the importance of various factors to these kinds of decisions; although generation is clearly relevant, individuals of any age can have attitudes or other characteristics that predispose them in one direction or another. Accordingly, it is appropriate to use an analysis method that does not deterministically assign individuals to one category or another, but rather specifies a probabilistic model for belonging to various categories, based on a number of observed traits including attitudes as well as age *per se*.

To achieve this goal, we use a custom designed travel survey administered in Fall 2018 in California that contains a rich array of variables facilitating our analysis. We propose a joint (trivariate) latent class (JLC) modeling methodology which not only readily allows for the joint modeling of multiple variables of different types, but, in contrast to more conventional trivariate models, provides insight into the correlations between the unobserved (latent) factors of the univariate models. The unique dataset and methodology of this study, therefore, can further help shed light on the factors influencing ridehailing usage frequency, vehicle ownership, and expectations to change vehicle ownership, and how these decisions tend to interact within different latent population groups.

The rest of this chapter is organized as follows: in the next section, we present a summary of the literature on ridehailing usage, vehicle ownership, and expectations/decisions to change vehicle ownership levels and how the current study fits within the existing literature. Section 4.4 discusses the details of the survey and the resulting dataset used in this study, and how it helps facilitate our analysis. In Section 4.5, we present the JLC modeling framework proposed in this chapter, and how it compares against the conventional joint models often used in travel behavior research. Section 4.6 presents the modeling results and discusses how the JLC model can be interpreted within the context of this study. We further discuss the results and their implications in Section 4.7 and close the chapter with a summary of the findings and concluding remarks in Section 4.8.

4.3 Literature review

The literature on each of the topics included in this study is fairly extensive, and in the case of vehicle ownership and vehicle ownership dynamics dates back several decades. The intent of this section, subsequently, is not to provide an in-depth and extensive review of the literature in each area, but to briefly summarize the knowledge in each field and discuss the more relevant studies in more depth.

4.3.1 Ridehailing usage frequency

The growing body of literature on ridehailing adoption, especially those studies conducted in the US and Canada, report the younger, well-educated, and urbanite travelers as more likely to be among ridehailing users (Tirachini, 2019). The studies on ridehailing usage frequency, however, are comparatively fewer, with results that sometimes point to different conclusions. Alemi, Circella, Mokhtarian, and Handy (2019) estimated ordered probit models of ridehailing usage frequency, and found sociodemographics to be rather weak predictors of usage frequency. Their results point to long-distance travel, attitudes toward car ownership, and willingness to pay to reduce travel time to be strongly associated with ridehailing usage. Some other studies, however, point to age and income as also being among the significant predictors of ridehailing usage frequency (Sikder, 2019; Tirachini & del Río, 2019), with the younger or more affluent tending to be more frequent ridehailing users. On the other hand, evidence from New York and Los Angeles, U.S., points to lower-income neighborhoods as producing more frequent users of ridehailing (Atkinson-Palombo, Varone, & Garrick, 2019; Brown, 2018). There is, therefore, a clear need for further investigation of ridehailing usage frequency (and of its relationships with the other dependent variables of interest that are the object of investigation in this study).

4.3.2 Vehicle ownership and availability

Vehicle ownership has been an important area of research in the transportation field for the past few decades, a topic with important implications for public health (Giles-Corti et al., 2016), job accessibility (Gao, Mokhtarian, & Johnston, 2008), travel demand modeling (Cervero, 2006), and air quality (Kitamura, Pas, Lula, Lawton, & Benson, 1996). This variable has been studied in different forms: many studies directly model the number of vehicles owned by a household (Bhat & Pulugurta, 1998), while some (including the investigation reported here) study a measure of household vehicle availability such as the number of household vehicles per licensed driver, or a vehicle deficiency measure such as having fewer vehicles than drivers (Blumenberg, Brown, & Schouten, 2018).

Considering the nature of the VO variable, the literature offers various modeling frameworks for its study, including linear regression, count, ordinal, or multinomial logit (probit) models. The explanatory variables used with these models often include sociodemographics and built environment characteristics. Those living in higher income households with higher numbers of workers and licensed drivers tend to own more cars (Bhat, 1998; Potoglou & Kanaroglou, 2008), and households living in more urban areas tend to own fewer cars than their rural counterparts (Bento, Cropper, Mobarak, & Vinha, 2005; J. M. Dargay, 2002). Several studies, in addition, have implemented various versions of the aforementioned modeling techniques to account for heterogeneity in the data. Anowar, Yasmin, Eluru, and Miranda-Moreno (2014), for instance, used a latent class modeling framework to study vehicle ownership in Quebec, Canada, and identified two latent segments of transit independent and transit friendly travelers, with each segment showing distinct modeling coefficients. Kim and Mokhtarian (2018), using a similar framework, identified two latent segments of auto-oriented and urbanites, and reported built environment factors as more influential in vehicle ownership decisions of the latter class than in those of the former class. In both studies, accounting for heterogeneity in modeling vehicle ownership resulted in a superior model fit.

4.3.3 Intentions/decisions to change vehicle ownership levels

The dynamics of vehicle ownership is another important area of transportation research, since change in a household's level of vehicle ownership has implications for its overall mobility and mode choice. The availability of more large-scale panel datasets has engendered more studies on this topic, with research showing that household life-cycle, current status of vehicle ownership, life events, and residential relocation all contribute to change in household vehicle ownership (Clark, Lyons, & Chatterjee, 2016). J. M. Dargay and Vythoulkas (1999), using data from annual Family Expenditure Surveys in the UK, reported that vehicle ownership increases as the head of household grows older until 50 years old, and then decreases. In another study, J. Dargay and Hanly (2007) used the British Household Panel survey and reported current vehicle ownership levels to be strongly associated with future vehicle ownership levels, and that the probability of a decline in vehicle ownership is higher in young (18-24 years old) and old (over 65 years old) households. Clark, Chatterjee, and Melia (2016) highlighted the influence of different life events on vehicle ownership, reporting that changes such as entering the work force are associated with an increase in vehicle ownership, while having a child showed an association with both an increase of vehicle ownership from one to two, and also a decrease of vehicle ownership from two to one. Yamamoto (2008), using French and Japanese datasets, reported on the influence of residential relocation in addition to life events on vehicle ownership, concluding that relocation of younger households is associated with a decrease in vehicle ownership. Cao, Mokhtarian, and Handy (2007) estimated a quasi-panel model using movers in their sample, to investigate the effects of built environment on changes in vehicle ownership. They reported that, most importantly, income and the number of driving-age household members before moving and increases in those variables after moving are associated with increases in vehicle ownership. Mishra et al. (2019), in the absence of panel data, proposed a method for their cross-sectional California sample that controls for self-selection and simultaneity bias and used it to estimate the impact of carsharing on changes in household vehicle ownership. They reported that, after controlling for various sources of bias, approximately one out of every six households enrolled in carsharing in their sample shed one vehicle due to the use of carsharing.

While the studies above investigate, after the fact, *decisions* to change vehicle ownership levels, a number of other studies (including the present one) use prospective *expectations/intentions* to change vehicle ownership. These studies are generally motivated either by a lack of available panel data, or by the novelty of the phenomenon under study whose impact is yet to come to pass. In any case, investigating people's intentions or expectations with regard to their vehicle ownership change can provide valuable behavioral insights. Kim, Ko, and Park (2015), for instance, investigated the willingness to dispose of a current vehicle among a sample of participants in an electric vehicle sharing program, and reported younger, lower-income individuals, or singles (among other characteristics) to be more likely to be willing to dispose of a current vehicle. Among other examples of these studies, Luke (2018) investigated the factors influencing car ownership intentions among a sample of South African students. Kim, Mokhtarian, and Circella (2020) studied the expectation to change vehicle ownership in an AV future among a sample of Georgians in the United States. Menon et al. (2017) studied a convenience sample's expectation of the potential impacts of shared autonomous vehicles on their household's vehicle ownership, and Sigurdardottir, Kaplan, and Møller (2014) studied the intentions and motivations underlying the decisions to obtain a driving license and own vehicles.

4.3.4 *Interaction of ridehailing usage and vehicle ownership*

The interaction of ridehailing and vehicle ownership has been another topic of great interest in the literature. Clewlow and Mishra (2017), for instance, asked the ridehailing respondents in their sample (of seven major US cities) whether they had made any decisions to get rid of a vehicle, and reported that 91% responded no change was made, and only 9% indicated they had disposed of one or more vehicles. The direction of causality between these two variables, however, can often be hard to elucidate; in other words, while for some a low level of vehicle ownership may prompt a higher usage of ridehailing, for others having access to ridehailing services may prompt a decision to decrease vehicle ownership levels. Most studies in the literature, however, often sidestep the possible bidirectional nature of this relationship, and use modeling techniques that tend to accommodate only one direction. For instance, Conway et al. (2018) used the U.S. 2017 National Household Travel Survey (NHTS) and applied a logistic regression model to estimate predictors of ridehailing adoption, with results pointing to a negative impact of vehicle ownership on ridehailing adoption. Sabouri et al. (2020) used the same dataset and estimated both a multilevel Poisson and a random forest model to study the predictors of vehicle ownership, and pointed to a negative impact of ridehailing on vehicle ownership. Dias et al. (2017) used the 2014-2015 Puget Sound Regional Travel Survey and estimated bivariate ordered probit models of ridehailing and carsharing usage. Their results point to the built environment-mediated influence of vehicle ownership on ridehailing usage, with a clear negative relationship existing in low density neighborhoods. Tirachini and del Río (2019), using a 2017 intercept survey in Santiago de Chile, estimated a generalized ordered logit model of ridehailing usage, but did not find a statistically significant impact of vehicle ownership levels on ridehailing usage. On the other hand, Gong et al. (2017) used a dataset of new vehicle registrations in China, and investigated how the timing of Uber entry to the market impacted vehicle purchases (representing the opposite direction of causality, namely that ridehailing influences vehicle ownership). Their findings point to a significant positive impact of Uber entry on vehicle purchases. Ward at al. (2021) also mirror similar findings in the U.S. using the NHTS 2009-2017 data, although a previous study by a similar group of authors (Ward et al, 2019) who studied vehicle ownership at the state level pointed to the opposite effect.

4.4 Dataset and variables

The dataset used in this study was collected in Fall 2018 in the state of California through a survey designed by a team of researchers at UC Davis and Georgia Tech. The survey was designed to extend a similar effort carried out in 2015 within the same geography by the same team, aiming to add a longitudinal dimension to understanding changing travel behavior and attitudes among the population (Circella, Matson, Alemi, & Handy, 2019). The data collection was accomplished through a mixed sampling method including stratified random sampling (mailing out a paper version of the survey to 30,000 randomly-selected households in the state), recruitment through online opinion panels, and reaching out to the same respondents who participated in the 2015 version of the study. The survey collected data on a wide range of travel-related topics, including personal attitudes and lifestyles; use of ICT and adoption of online social media; residential location and living arrangements; commuting and other travel patterns; auto ownership; awareness, adoption and frequency of use of several types of shared-mobility services; awareness of and opinions on autonomous vehicles; and sociodemographic traits. The sample size of the dataset is approximately 3,835 cases. Considering that we are also modeling ridehailing usage, we excluded those who expressed that they are not familiar with ridehailing services, and conducted our analysis on the rest of the dataset (N=3,141). Table 17 shows a summary of the characteristics of the dataset.

Table 17 Selected sociodemographic characteristics of the sample (N =3,141)

Variables	Characteristics	N	Share
Gender	Male	1,472	46.9%
	Female	1,661	52.8%
	Transgender	8	0.03%
Age	18-37 years old	927	29.5%
	38-53 years old	995	31.7%
	54-72 years old	959	30.5%
	73-90 years old	260	8.3%
Race	White	2,530	80.5%
	Asian	425	13.5%
	Black	143	4.6%
	Other	43	1.4%
Annual household income	< US $50K	937	29.8%
	US $50K- $100K	1,016	32.3%
	> US $100K	1,188	37.8%
Education	Bachelor’s degree or higher	1,842	58.7%
	Some college/technical degree	983	31.3%
	High school diploma/lower	296	9.4%
Household (HH) size	Single-person HH	588	18.7%
	Two-person HH	1,178	37.5%
	Three-person HH	561	17.9%

Table 17 Cont'd

	Four-person+ HH	814	25.9%
Employment	Worker (full/part time/two jobs)	2,089	66.5%
	Not a worker (Do not work/retired/ homemaker/volunteer)	1,052	33.5%
Student	Student (full/part time)	362	11.6%
Built environment	Urban	1,042	33.2%
	Suburban	1,473	46.9%
	Rural	626	19.9%
Carsharing adoption	Carsharing adopter	161	5.1%
Car ownership	Zero vehicle	168	5.3%
	One vehicle	891	28.4%
	Two vehicles	1,239	39.4%
	Three+ vehicles	843	26.8%

In addition to the socioeconomic and travel behavior variables, our dataset, as mentioned, also contains a rich array of attitudinal/perception statements. In order to leverage these variables in our analysis most effectively, we conducted a set of exploratory factor analyses (principal axis factoring with oblique rotation) to reduce the dimensionality and better capture the attitudinal and perception constructs behind those statements. We used the Bartlett method to generate the corresponding factor scores. In the following subsection, we briefly introduce the resulting constructs later used in our analysis.

4.4.1 Exploratory factor analysis (EFA) results

The survey included 30 attitudinal and lifestyle statements related to travel behavior. We extracted 9 attitudinal constructs using the EFA approach with oblique rotation, with the resulting constructs explaining 57.3% of the variance of the underlying items. Table 18 presents the resulting constructs that were used further in our analysis.

The *pro-sustainability* construct, as shown in Table 18, captures respondents' opinions toward stronger governmental or personal action to help the environment and remedy traffic congestion through better transit and fewer cars on the road. The *car enthusiast* construct measures the extent to which a respondent would definitely want to own a car. The *pro-urban* construct reflects favorability toward living in urban neighborhoods where houses tend to be smaller but mixed-use development and transit stops are more prevalent. The *eco-minimalist* attitude represents favorability toward minimizing one's possessions and being committed to live an environmentally friendly life. With respect to the *busy car dependent* attitude, people with higher scores on this construct tend to have busier lifestyles where their transportation needs cannot be met using transit and a reliance on the personal car is dominant. Finally, the *life adrift* construct is negatively associated with life satisfaction, and positively associated with present uncertainty about one's career.

Table 18 Summary of exploratory factor analysis (EFA) of travel-related attitudes used in this study

Statement[1]	Pattern Matrix Loading	Statement	Pattern Matrix Loading
Pro-sustainability		*Car enthusiast*	
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.92	I definitely want to own a car.	0.76
We should raise the price of gasoline to provide funding for better public transportation.	0.85	I am fine with not owning a car, as long as I can use/rent one any time I need it.	-0.42
The government should put restrictions on car travel in order to reduce congestion.	0.46	I prefer to be a driver rather than a passenger.	0.36
I am willing to pay a little more to purchase a hybrid or other clean-fuel vehicle.	0.43		
I am committed to an environmentally-friendly lifestyle.	0.37		
Pro-urban		*Eco-minimalist*	
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.	-0.78	I prefer to minimize the material goods I possess.	0.47
I prefer to live close to transit even if it means I'll have a smaller home and live in a more crowded area.	0.51	I am committed to an environmentally-friendly lifestyle.	0.47
I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	0.30		
Busy car dependent		*Life adrift*	
My schedule makes it hard or impossible for me to use public transportation.	0.78	I am generally satisfied with my life.	-0.65
Most of the time, I have no reasonable alternative to driving.	0.46	I'm still trying to figure out my career (e.g. what I want to do, where I'll end up).	0.52
I am too busy to do many things I'd like to do.	0.38	I am uncomfortable being around people I do not know.	0.34

[1] Variables are on a 5-level Likert-type scale (strongly disagree to strongly agree).
The highest-magnitude correlation between pairs of factor scores is -0.34.

4.4.2 Dependent variables

4.4.2.1 Ridehailing usage survey

The survey recorded respondents' answers to their ridehailing usage frequency by providing the following options: "I am not familiar with [this service]", " it's familiar but I've never used it", "I used it in the past, but not anymore", "I use it less than once a month", "I use it 1-3 times a month", "I use it 1-2 times a week", and "I use it 3 or more times a week". As mentioned, we excluded those who reported they were not familiar with ridehailing services from our analysis. Furthermore, the shares of those reporting using ridehailing "1-2 times a week" and "3 or more times a week" were very small at 3.8% and 1.3%, respectively, and we subsequently decided to merge these levels with the "1-3 times a month" level to avoid estimation issues (untenable coefficients) and called this new merged level *regular users*. Similarly, those who use ridehailing less than once a month were categorized as *infrequent users*, and those who reported they are not current users were categorized as *not a user*. Table 19 shows more details on the ridehailing usage variable used in this study.

Table 19 Distribution of the ridehailing usage variable of this study (N=3141)

Variable used in the model	Underlying levels	$N_{\text{Underlying items}}$ (%)	$N_{\text{Variable used in the model}}$ (%)
Not a user	It's familiar but I've never used it.	1342 (42.7%)	1512 (54.5%)
	I used it in the past, but not anymore.	370 (11.8%)	
Infrequent user	I use it less than once a month.	861 (27.4%)	861 (27.4%)
Regular user	I use it 1-3 times a month.	407 (13.0%)	568 (18.1%)
	I use it 1-2 times a week.	120 (3.8%)	
	I use it 3 or more times a week.	41 (1.3%)	

4.4.2.2 Vehicle availability

We decided to use a measure of vehicle (un)availability in our modeling as opposed to a simple vehicle ownership variable, since vehicle availability is a more useful measure of a household's mobility status (Cambridge Systematics, 1997), and can be more insightful in our context where its relationship with ridehailing usage is of interest. We, therefore, defined a binary measure of *household vehicle deficiency* using the number of licensed drivers in a household vs. the number of vehicles owned by it. A household owning fewer vehicles than its number of licensed drivers is coded as "1" or "vehicle deficient", and "0" otherwise. The share of vehicle deficient households in our dataset is 17.6%.

4.4.2.3 Intentions to change vehicle ownership

The survey used in this analysis also collected data on what respondents expected will happen to their household's car ownership over the next three years. The options available included: "increase the number of cars", "decrease the number of cars", "keep the same total but replace one or more cars", "No change", and "I do not know". Although we could have used the variable as is in a categorical format, the desire to focus on level, in addition to the added model parameters in return for small additional interpretability, prompted a recoding of this variable. Table 20 shows the distribution of this variable in our model.

Table 20 Distribution of the intentions to change vehicle ownership levels in this study (N=3136)

Variable used in the model	Underlying categories	N Underlying categories (%)	N Variable used in the model (%)
Decrease intention	Decrease the number of cars	196 (6.2%)	196 (6.2%)
No/unclear intention	Keep the same total but replace one or more cars	1000 (31.8%)	2542 (80.9%)
	No change	1206 (38.4%)	
	I do not know	336 (10.7%)	
Increase intention	Increase the number of cars	398 (12.7%)	398 (12.7%)

4.5 Methodology

Joint bivariate or trivariate probit models are traditionally formulated using latent continuous error terms representing the unaccounted-for factors and allowing for correlation between the error terms. The mathematical formulation of a traditional trivariate probit model, without loss of generalizability for lower or higher order models, may be written as (Chib & Greenberg, 1998):

$$p(Y_1 = y_1, Y_2 = y_2, Y_3 = y_3|X) = \iiint_{-\infty}^{+\infty} p(Y_1, Y_2, Y_3|X, \varepsilon_1, \varepsilon_2, \varepsilon_3) f(\varepsilon_1, \varepsilon_2, \varepsilon_3|X)\, d\varepsilon. \quad (21)$$

In Eq. (21), Y_i denotes the dependent variables to be modeled jointly, X is the vector of explanatory variables, and ε_i is the error term associated with each dependent variable. Assuming the conditional mutual independence of the Y_i variables in addition to the independence of the error terms from the observed variables, Eq. (21) will equal:

$$p(Y_1 = y_1, Y_2 = y_2, Y_3 = y_3|X) =$$

$$\iiint_{-\infty}^{+\infty} p(Y_1|X, \varepsilon_1) p(Y_2|X, \varepsilon_2) p(Y_3|X, \varepsilon_3) f(\varepsilon_1, \varepsilon_2, \varepsilon_3) d\varepsilon. \quad (22)$$

Assuming a normal distribution for the error terms, and a simple variable transformation on the ε_i, Eq. (22) can be written as a trivariate normal CDF:

$$p(Y_1 = 1, Y_2 = 1, Y_3 = 1|X) = \int_{-X\beta_1}^{+\infty} \int_{-X\beta_2}^{+\infty} \int_{-X\beta_3}^{+\infty} \phi\, (\varepsilon_1, \varepsilon_2, \varepsilon_3, \rho_{12}, \rho_{13}, \rho_{23}) d\varepsilon_1 d\varepsilon_2 d\varepsilon_3,$$

(23)

where β_i is the unknown vector of model coefficients associated with dependent variable Y_i, ρ_{ij} is the correlation between pair i and j of εs, and ϕ is the density function for the trivariate normal distribution with mean vector 0 and variance-covariance (correlation) matrix given by the ρ_{ij}s.

Different extensions of this traditional model have been proposed, such as joint models that account for heterogeneity by allowing for random coefficients for the observed variables (Singh & Ullah, 1974), or joint models that account for heterogeneity in the correlations among the error terms (Heydari, Fu, Miranda-Moreno, & Jopseph, 2017). In this study, however, we use categorical latent variables to capture parameter heterogeneity in a joint model of ridehailing usage frequency, vehicle availability, and expectations to change vehicle ownership. Specifically, we identify a finite number of latent classes associated with each of those outcomes, where each outcome model has different coefficients for each latent class. Then, instead of connecting the three outcome variables through allowing correlations among their error terms (i.e. among the unobserved characteristics influential to those outcomes), we connect them through allowing relationships among the binary variables indicating membership in the latent classes associated with each outcome, while assuming that the outcome variables are conditionally independent *given* their associated latent classes and explanatory variables (see Section 4.6.1 for additional explanation).

The advantages of using the Latent Class (LC) framework to jointly model variables as opposed to the other abovementioned approaches are threefold. Firstly, using an LC framework to account for unobserved heterogeneity better enables a post-hoc investigation of the existence and nature of discrete population segments having different coefficients for each outcome model, compared to the alternative mixed logit framework, which arguably provides a more convoluted and abstract approach to inferring coefficient values for a given segment or individual in the population (Kim and Mokhtarian, 2018). Secondly, using this proposed methodology, we can jointly model variables of different types using any modeling framework easily (in our context, ordinal, binary, and 3-level categorical, all through the logit modeling framework) while incorporating the additional behavioral insight obtained by accounting for the heterogeneity in the data. The alternative joint modeling approaches described at the beginning of this section are more limited in this regard by the viability of the joint probability distribution of the error terms. Lastly, this proposed JLC approach allows for the computation of goodness-of-fit statistics for each outcome model separately, while the alternative approaches preclude the computation of such measures for each dependent variable.

We now turn to the mathematical definition of the JLC model. Following a similar approach as in Eqs. (21-22), we define an LC trivariate model as:

$$p(Y_1, Y_2, Y_3|X) = \sum_C p(C|X)p(Y_1, Y_2, Y_3|X, C), \tag{24}$$

where C denotes the LC variable. We further separate the vector of explanatory variables, X, into two (possibly overlapping) subsets denoted as Z and X', where the Z vector denotes the variables influencing the formation of the latent classes, and X' encompasses those variables directly influencing the dependent variables. Following this notation, and by assuming a conditional mutual independence between the dependent variables Y_i given the explanatory variables and the latent classes, we will have:

$$p(Y_1, Y_2, Y_3|X) = \sum_C p(C|Z)p(Y_1|X', C)p(Y_2|X', C)p(Y_3|X', C). \tag{25}$$

The univariate (conditional) distribution of each dependent variable in Eq. (25), i.e. $p(Y_i|X', C)$, also known as an outcome model, is formulated based on the type of the dependent variable. In this study, we use an ordinal logit model for ridehailing usage frequency, a binary logit model for the vehicle deficiency status of a household, and a multinomial logit (MNL) model for the expectations to change vehicle ownership levels. Furthermore, the conditional discrete distribution of the LC variable, i.e. $p(C|Z)$, may be modeled using an MNL formulation.

The abovementioned conditional independence (CI) assumption between the Y_is can be checked by computing the associated bivariate residuals (BVR) in the model (Vermunt & Magidson, 2013). A statistically significant BVR indicates that there still remains significant correlation between the dependent variables in addition to what is already controlled for through the latent classes and explanatory variables. There are three potential remedies if the CI assumption is violated in this model: (1) control for as much observed variability as the dataset allows (or decreasing the omitted variable bias by including additional explanatory variables), (2) increase the number of LCs (possibly resulting in a decrease in the variability within classes), (3) control for correlations among the within-class model error terms (or estimate a conventional bivariate/trivariate model whose error correlations are conditional on the LCs (Eusebi, Reitsma, & Vermunt, 2014))[9].

The JLC model defined in Eq. (25) assumes that all the dependent variables (Y_i) are associated with the same LC variable (C), while it is conceivable that each Y_i should be

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[9] The formulation of such a model (in the bivariate case), following a similar methodology as above, would be:
$p(Y_1, Y_2|X) = \sum_c p(c|Z)p(Y_1, Y_2|c, X') = \sum_c p(c|Z) \iint p(Y_1|c, X', \epsilon_1)p(Y_2|c, X', \epsilon_2)f(\epsilon_1, \epsilon_2|c)\, d\epsilon_1\, d\epsilon_2$,
with $f(\epsilon_1, \epsilon_2|c)$ denoting the conditional bivariate normal distribution of the error terms within each LC.

influenced by a separate LC variable of its own. Subsequently, we extend the model of Eq. (25) to accommodate multiple LC variables:

$$p(Y_1, Y_2, Y_3|X) = \sum_{C_1} \sum_{C_2} \sum_{C_3} p(C_1, C_2, C_3|Z) p(Y_1, Y_2, Y_3|X', C_1, C_2, C_3). \quad (26)$$

Assuming the same CI assumption between the dependent variables, we may have:

$$p(Y_1, Y_2, Y_3|X) = \sum_{C_1} \sum_{C_2} \sum_{C_3} p(C_1, C_2, C_3|Z) p(Y_1|X', C_1)\, p(Y_2|X', C_2) p(Y_3|X', C_3). \quad (27)$$

The joint conditional distribution of the LCs in Eq. (27), also known as the membership model, can be modeled as a product of conditional probabilities, with each univariate probability formulated using an MNL model:

$$p(C_1, C_2, C_3|Z) = p(C_1|C_2, C_3, Z) p(C_2|C_3, Z) p(C_3|Z). \quad (28)$$

As Eq. (28) shows, the probability of belonging, for example, to a specific level of LC variable C_1 is not only dependent on a set of observed covariates Z, but also on the probabilities of belonging to specific levels of LCs C_2 and C_3. This model formulation, therefore, allows us to gain a deeper insight into how different latent groups interact with each other.

The log-likelihood function of Eq. (25) or (27) may be maximized using a combination of Expectation-maximization (EM) and Newton-Raphson (NR) methods. We coded the model in LatentGold 5.1, and used the software to solve for the unknown parameters.

The estimated LL of this model will, naturally, be associated with the full trivariate model rather than each univariate model, hence precluding the computation of separate traditional goodness-of-fit statistics for each of the models. In our JLCM, we can obtain the univariate LL of each model by marginalizing the joint probability of Eq. (27). To start, we can write Eq. (27) as:

$$p(Y_1, Y_2, Y_3|X) =$$

$$\sum_{C_1}\sum_{C_2}\sum_{C_3} p(C_1|C_2, C_3, Z)p(C_2|C_3, Z)p(C_3|Z)p(Y_1|X', C_1)\, p(Y_2|X', C_2)p(Y_3|X', C_3)$$

$$= \sum_{C_3} p(C_3|Z)p(Y_3|X', C_3)\sum_{C_2} p(C_2|C_3, Z)\,(Y_2|X', C_2)\sum_{C_1} p(C_1|C_2, C_3, Z)p(Y_1|X', C_1).$$

(29)

To obtain the marginal probability of Y_3, as an example, we marginalize the joint probability of Eq. (29) over Y_1 and Y_2:

$$p(Y_3|X) =$$

$$\sum_{Y_1}\sum_{Y_2}\sum_{C_3} p(C_3|Z)p(Y_3|X', C_3)\sum_{C_2} p(C_2|C_3, Z)\, p(Y_2|X', C_2)\sum_{C_1} p(C_1|C_2, C_3, Z)p(Y_1|X', C_1) =$$

$$\sum_{C_3} p(C_3|Z)p(Y_3|X', C_3)\sum_{C_2} p(C_2|C_3, Z)\,\left(\sum_{Y_2} p(Y_2|X', C_2)\right)\sum_{C_1} p(C_1|C_2, C_3, Z)\left(\sum_{Y_1} p(Y_1|X', C_1)\right).$$

(30)

Since $\sum_{Y_2} p(Y_2|C_2, X') = 1$ and $\sum_{Y_1} p(Y_1|C_1, X') = 1$, we have:

$$p(Y_3|X) = \sum_{C_3} p(C_3|Z)p(Y_3|X', C_3)\sum_{C_2} p(C_2|C_3, Z)\sum_{C_1} p(C_1|C_2, C_3, Z). \qquad (31)$$

Similarly, in Eq. (31) we have $\sum_{C_1} p(C_1|C_2, C_3, Z) = 1$ and $\sum_{C_2} p(C_2|\, C_3, Z) = 1$. The (conditional) marginal probability of Y_3 will then be:

$$p(Y_3|X) = \sum_{C_3} p(C_3|Z)p(Y_3|X', C_3). \tag{32}$$

Similarly, the (conditional) marginal distributions associated with Y_2 and Y_1 can be calculated as:

$$p(Y_2|X) = \sum_{C_2} p(C_2|C_3, Z)p(Y_2|X', C_2) \quad \text{and,} \tag{33}$$

$$p(Y_1|X) = \sum_{C_1} p(C_1|C_2, C_3, Z)p(Y_1|X', C_1)\ . \tag{34}$$

To obtain the marginal LL of each univariate model, we used the estimated parameters of the JLC model (Eq. (27)) in conjunction with the marginal probabilities Eqs. (32-34), and computed the LL of the models.

4.6 Results

In discussing the results below, we first present the membership model portion of the analysis, and then focus on the outcome models. We divided the dataset into training and test sets (approximately 80%, 20% of the sample, respectively) to be able to check for improvements in model prediction accuracy as well. In deciding the number of latent clusters associated with each dependent variable, we firstly estimated separate univariate LC regression models for each variable, and identified a suitable number of latent clusters based on each model's information criteria (IC) (Magidson & Vermunt, 2004) and interpretation. We subsequently started from the identified number of clusters in the previous step and varied that number for each dependent variable, looking for improvement in the joint model's IC, prediction accuracy, and overall interpretability, in addition to checking for violation of the CI assumption.

We used attitudinal factors (in addition to age, in the case of ridehailing usage frequency) as the model covariates (Z) to be able to define the LCs as “lifestyle segments”, and left the other sociodemographics and travel behavior variables to the outcome portion of the model. Figure 16 shows a schematic of the JLC model of this study.

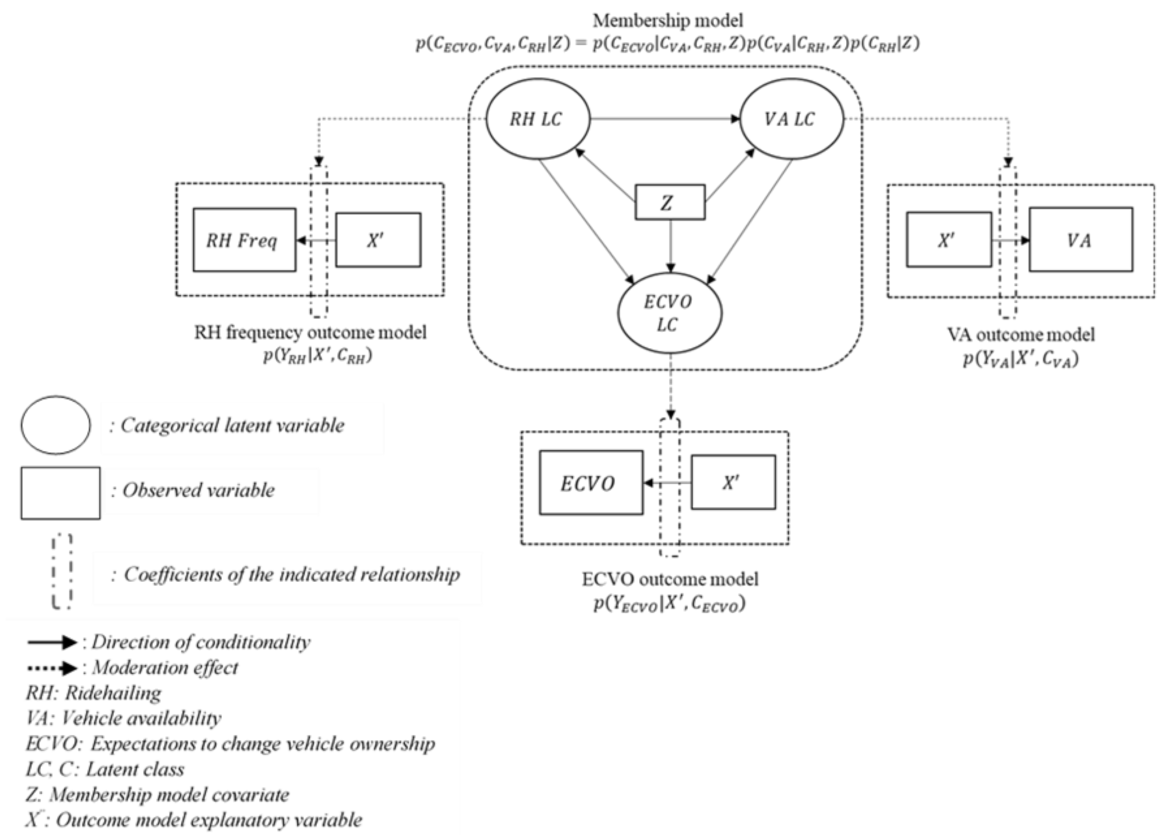

Figure 16 Schematic of the joint (trivariate) latent class (JLC) model of this study

4.6.1 Membership model

Figure 17 shows a more detailed schematic of the membership model of this study. We tested different covariate (Z) specifications and retained only statistically significant effects in the final model. Furthermore, the directions of conditionality among the LC variables were determined largely based on empirical grounds. It is relevant to note that our modeling structure does not assume causal relationships among the dependent variables themselves, but establishes correlations among them through their associated LC variables. Establishing directions of causality (or more precisely here, conditionality) among the LC variables themselves, however, is a less straightforward matter, given their more abstract definition. Although assuming bidirectional correlations among the LC variables would have been a more straightforward assumption, we could not establish such a formulation mathematically in our model as defined in Section 4.5. We, therefore, empirically tested different conditionality structures among the LC variables (associated with different chain rule setups in Eq. 28), and chose the one resulting in the best model fit. The results showed that the specification where memberships in the LCs associated with ridehailing and vehicle availability influenced membership in the LC associated with expectations to change vehicle ownership had a superior model fit.

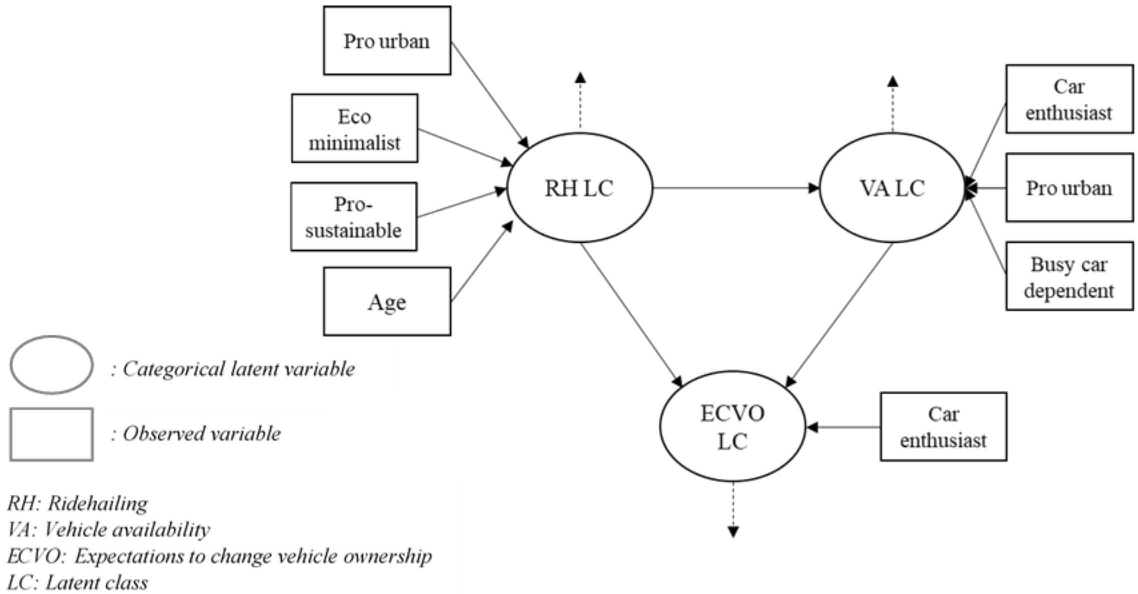

Figure 17 The schematic of the membership sub-model of this study

Table 21 shows a summary of the descriptive statistics of the membership model. In each vertical section, presenting the respective profiles of the LCs associated with each of the three outcome variables, the bolded rows highlight the values of the statistically significant variables directly involved in the class membership modeling for each associated LC variable. We should note that given the structure of the membership model of this study (defined in Eq. 28), the covariates that are involved in modeling the RH LC variable also indirectly influence the VA LC and ECVO LC variables formation, as do covariates involved in modeling the VA LC variable which similarly exert an indirect influence on the ECVO LC variable. Accordingly, such covariates may have a substantial overall influence on the ECVO LC and VA LC variables (manifested in their averages being noticeably different across the latent clusters of the VA and ECVO LC variables) even though their direct statistical influence on those variables is insignificant.

Table 21 Summary of descriptive statistics of the Joint Latent Class membership sub-model ($N_{Training\ set}$=2,412)

Model variables	Descriptive statistics Variable means/share per Class						
	RH usage frequency LC			Vehicle deficient household LC		Expectations to change vehicle ownership LC	
	Younger Eco-friendly (31.4%)	Younger Non-eco-friendly (29.0%)	Older Car Enthusiast (39.6%)	Car Enthusiast & Dependent (58.5%)	Non-car Dependent Lower Income (41.5%)	Non-eco-friendly Car Enthusiast (29.6%)	Eco-friendly Stable in Life (70.4%)
Outcome variables							
RH usage frequency *(ordinal)*							
Not a user	**0.124**	**0.728**	**0.740**	0.556	0.524	0.537	0.545
Infrequent user	**0.325**	**0.250**	**0.258**	0.290	0.258	0.267	0.281
Regular user	**0.552**	**0.022**	**0.002**	0.154	0.218	0.197	0.174
Vehicle deficient HH *(binary)*	0.203	0.223	0.131	**0.013**	**0.416**	0.296	0.132
Intentions to change HH's VO *(categorical)*							
Intention to decrease	0.049	0.036	0.073	0.064	0.042	**0.022**	**0.069**
Undecided or keep the same	0.812	0.695	0.922	0.879	0.741	**0.581**	**0.923**
Intention to increase	0.139	0.269	0.005	0.058	0.216	**0.398**	**0.009**
Model covariates							

Table 21 Cont'd

Age	**40.96**	**41.63**	**59.33**	50.64	45.30	41.45	51.35
FS Pro-sustainable	**0.298**	**-0.209**	**-0.111**	-0.081	0.087	-0.051	0.006
FS Eco-minimalist	**0.107**	**-0.247**	**0.083**	-0.002	-0.011	-0.139	0.051
FS Pro-urban	**0.141**	**-0.362**	**0.116**	**-0.160**	**0.191**	-0.176	0.053
FS Car enthusiast	-0.161	0.016	0.112	**0.288**	**-0.409**	**0.096**	**-0.042**
FS Busy car dependent	-0.043	0.055	-0.015	**0.178**	**-0.259**	-0.038	0.011
Inactive covariates							
FS Life adrift	0.171	0.198	-0.254	-0.100	0.167	0.206	-0.071
HH income							
Low income HH (<$50K)	0.311	0.314	0.286	0.270	0.346	0.322	0.293
High income HH (>$100K)	0.409	0.338	0.374	0.403	0.334	0.356	0.382
Graduate degree or higher	0.221	0.198	0.259	0.241	0.213	0.205	0.240
Urban dweller[1]	0.403	0.331	0.296	0.297	0.400	0.352	0.334

[1] Defined based on the geocoded home addresses of the respondents and the classification presented by Salon (2015). This variable denotes a person living in urban or central city neighborhood types as defined in the Salon (2015) classification.

4.6.1.1 Latent classes associated with ridehailing usage frequency

The ridehailing usage frequency LC variable denominates three clusters. Cluster 1, or the Younger Eco-friendly, comprises 31% of the sample. Ridehailing regular users form the majority of this cluster, while the non-users' share is the smallest at 12.4%. The respondents in this cluster have an average age of approximately 41 years old, making them the youngest of the three clusters (although by a small margin compared to the second cluster). With respect to the other active covariates, this cluster defines itself as the most pro-sustainable, eco-minimalist, and pro-urban of all the ridehailing clusters. This cluster, in addition, is the least car enthusiast, and compatible with their average age, expresses a lower sense of life stability compared to the older Cluster 3. Moreover, the share of those living in vehicle deficient households, at 20.3%, is fairly similar to that of Cluster 2, but higher than Cluster 3, and the share of those who express an intention to increase their vehicle ownership, at 13.9%, is considerably lower than Cluster 2, yet substantially higher than Cluster 3. With respect to income, this cluster has the highest share of high incomes, while its share of low incomes is similar to that of Cluster 2 and higher than that of Cluster 3. Moreover, the share of the highly educated in this cluster is higher than for the similarly aged Cluster 2, but lower than for the older Cluster 3. Finally, the share of those in this cluster living in urban areas, at 40.3%, is the highest of all the clusters.

Cluster 2, or the Younger Non-eco-friendly, comprises a slightly smaller share of the sample, at 29%. It largely includes those who are not users of ridehailing (72.8%), with the share of infrequent and regular users at 25.0% and 2.2%, respectively. The average age of the respondents in Cluster 1 is approximately 41.6 years old, and they are on average the least pro-sustainable, eco-minimalist, and pro-urban of those in the sample. Their attitude toward car ownership is more positive than that of the approximately similarly aged Younger Eco-friendly, but less so than that of the older respondents of Cluster 3. With respect to inactive covariates (including the other dependent variables), we observe that this cluster has a slightly higher share of vehicle deficient households than do the Younger Eco-friendly. In terms of expectations to change vehicle ownership in the next three years, we see that this cluster contains the largest share (at 26.9%) of those who express an intention of increasing, and the smallest share (3.6%) of those who express an expectation of decreasing. Furthermore, this cluster, on average, and consistent with their younger average age, are more life adrift than the older Cluster 3, but are fairly on par with the similarly aged Younger Eco-friendlies. In terms of income and education, the respondents in this cluster are comparatively lower income and lower educated than those of the other two clusters. Finally, with respect to the built environment, we see that the share of those living in urban areas in this cluster, at 33.1%, is in between those of the (similarly aged Cluster 2) and (older) Cluster 3.

Finally, Cluster 3, or the Older Car enthusiast, contains 40% of the sample. In this group we see, on average, older respondents whose share of regular ridehailing users is close to zero. Their attitudes on sustainability, eco-minimalism, and urban living are in between those of Clusters 1 and 2, while they characterize themselves as the most car enthusiast and life stable among the clusters. The share of those who report an increase intention toward vehicle ownership is close to zero, while the share of those with a decrease intention, albeit still relatively small, is the largest of all the clusters. In terms of income, the respondents in this cluster have the lowest share of low incomes, while their share of high incomes is in between those of Clusters 2 and 3. Furthermore, this cluster has the highest share of the highly educated, in addition to the lowest share of urban dwellers.

4.6.1.2 Latent classes associated with vehicle availability

The vehicle availability LC variable designates two clusters. Cluster 1, the Car enthusiast & Dependent cluster, involves about 58% of the sample. Its share of vehicle deficient households is quite small at approximately 1.3%, with attitudes against urban living and for car ownership considerably stronger than in the second cluster. Furthermore, this cluster is comparatively less pro sustainable but more life stable, and the share of those reporting an intention to increase their household's vehicle ownership levels is substantially lower than the other cluster's at 5.8%. In terms of socioeconomic status, this cluster is relatively higher income, with it having a lower share of low-income households (27.0%) and a higher share of high-income households (40.3%). Finally, the share of those living in urban areas, at 29.7%, is comparatively lower than in the other cluster.

Cluster 2, or the Non-car Dependent Lower Income cluster, contains the remaining 42% of cases. A substantial portion of the respondents in this cluster live in vehicle deficient households, and they are comparatively more pro-urban and less car enthusiast than those in Cluster 1. Furthermore, the share of those who express that their household intends to increase its vehicle ownership levels is comparatively higher at 21.6%, while the share of those expressing a decrease intent, at 4.2%, is relatively lower than that of Cluster

1. Finally, and as mentioned above, this cluster is comparatively lower income and lower educated, with a higher share of its respondents living in urban areas.

4.6.1.3 Latent classes associated with expectations of changing vehicle ownership

Finally, for the intentions to change vehicle ownership (in the next three years) variable, we identify two latent clusters. The Non-eco-friendly Car Enthusiast cluster, containing 30% of the sample, contains a relatively larger share of those with an intention to increase their household's vehicle ownership (at 39.8%) compared to that of Cluster 2 (the Non-eco-friendly Car Enthusiast cluster) at less than 1%. Furthermore, the share of those expressing an intention to decrease, at 2.2%, is also comparatively smaller than that of Cluster 2, where 6.9% express such an intention. This cluster, furthermore, contains a larger share of vehicle deficient households than Cluster 2 does (29.6% vs. 13.2%, respectively), and on average has respondents that are more car enthusiastic. The respondents in this cluster are also relatively less pro-sustainable, eco-minimalist, and pro-urban than the other cluster. Moreover, this cluster is a relatively lower income and lower educated group, with a slightly higher share of it living in urban areas.

4.6.1.4 The associations between the latent class variables

Table 22 shows a summary of the parameters of the LC variables' association model. Considering that the dependent variables here are categorical LC variables, the coefficients are associated with an MNL model (with effect coding). For ease of presentation and discussion, we only include the parameters directly related to the LC associations here, and leave the detailed presentation of the results (such as constant terms and observed covariates' coefficients) to the Appendix C.

Table 22 Summary of the (MNL) membership model parameters of the associations between the latent class variables (N=2,412)

Explanatory variable	Clusters	Dependent variables			
		Vehicle deficient household LC		Expectations to change VO LC	
		Car Enthusiast & Dependent	Non-car Dependent Lower Income	Non-eco-friendly Car Enthusiast	Eco-friendly Stable in Life
		Coef. (S.E.)	Coef. (S.E.)	Coef. (S.E.)	Coef. (S.E.)
Ridehailing usage frequency LC	Younger Eco-friendly	-0.0010 (0.106)	0.0010 (0.106)	0.499^{**} (0.248)	-0.499^{**} (0.248)
	Younger Non-eco-friendly	-0.357^{*} (0.214)	0.357^{*} (0.214)	1.431^{***} (0.382)	-1.431^{***} (0.382)
	Older Car Enthusiast	0.358^{**} (0.171)	-0.358^{**} (0.171)	-1.930^{***} (0.501)	1.930^{***} (0.501)
Vehicle deficient household LC	Car Enthusiast & Dependent	–	–	-0.710^{**} (0.302)	0.710^{**} (0.302)
	Non-car Dependent Lower Income	–	–	0.710^{**} (0.302)	-0.710^{**} (0.302)

***, **, * denote a statistical significance of less than 0.01, 0.05, 0.10, respectively.

As Table 22 demonstrates, being a member of the "RH: Younger Non-eco-friendly" cluster increases the propensity to belong to the "VA: Non-car Dependent Lower Income" cluster, while this relationship, although positive in sign, is statistically and practically zero for the "RH: Younger Eco-friendlies". This positive association in the former case is as expected, since this cluster contains a higher share of vehicle deficient households than the others, and some of its other characteristics such as income level and ECVO align with this cluster. On the other hand, we see that belonging to the "RH: Older Car enthusiast" cluster positively and significantly increases the propensity to belong to the "VA: Car Enthusiast & Dependent" cluster.

Moreover, being a "RH: Younger Non-eco-friendly" or "RH: Younger Eco-friendly" member increases the propensity of belonging to the "ECVO: Non-eco-friendly Car Enthusiast" cluster. Comparing the coefficient sizes of the two RH cluster membership indicators, however, we see that (all else equal) the "RH: Younger Eco-friendlies" are less likely to belong to the "ECVO: Non-eco-friendly Car Enthusiast" cluster than the "RH: Younger Non-eco-friendlies". The "RH: Older Car enthusiasts", on the other hand, are more likely to belong with the "ECVO: Eco-friendly Stable in Life" cluster.

Finally, we see that, also as expected, being a member of the "VA: Non-car Dependent Lower Income" cluster increases the likelihood of belonging to the "ECVO: Non-eco-friendly Car Enthusiast" cluster, implying that those with lower existing vehicle availability tend to have a higher intention to increase their household's vehicle ownership.

4.6.2 Outcome models

In this section, we first discuss each of the outcome models of this study in turn, and then present the accuracy of the model with respect to the prediction of each dependent variable on the designated test set. As mentioned, the explanatory variables used in the outcome models include sociodemographics, built environment, and travel behavior variables.

4.6.2.1 Ordered logit model of ridehailing usage frequency

Table 23 shows the parameters of the ordered logit model of ridehailing usage frequency. Among the sociodemographic variables, we largely see intuitive results. Those living in low-income households are less likely to be among the more frequent users of ridehailing, while having a higher level of education is positively associated with a higher ridehailing usage level.

The built environment, moreover, shows a logical relationship with ridehailing usage frequency, with those living in urban areas more likely to be among the more frequent ridehailers. This relationship, however, is statistically weak in the “RH: Younger Non-eco-friendly” cluster, and further points to the difference between the “RH: Younger Eco-friendly” and “RH: Younger Non-eco-friendly” clusters.

With respect to other travel behaviors and opinions, we see that those with a more positive opinion about transit meeting their needs are also more likely to be among the more frequent ridehailers, although this positive impact is much weaker among the “RH: Younger Non-eco-friendlies”. This result implies that ridehailing may be drawing from the same pool of travelers as transit, although we cannot necessarily infer the complementary/ competitive nature of this relationship from this model. Finally, carsharing adopters across all three clusters are significantly more likely to use ridehailing services on a regular basis, likewise pointing to the similar pool of travelers that both ridehailing and carsharing have in common.

Table 23 Ordered logit outcome model of ridehailing usage frequency ($N_{training\ set}$=2,412)

Explanatory variables	RH Clusters: Younger Eco-friendly	RH Clusters: Younger Non-eco-friendly	RH Clusters: Older Car enthusiast
	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)
Low income HH	-1.110*** (0.230)	-4.387*** (0.887)	-1.101*** (0.302)
Holding a graduate degree or higher	0.713* (0.396)	0.588* (0.334)	0.713*** (0.23)
Urban dweller[1]	0.955*** (0.242)	0.183 (0.349)	0.455* (0.273)
Transit meets my needs[2]	0.238** (0.114)	0.026 (0.138)	0.260** (0.105)
Carsharing adopter	1.598* (0.934)	5.856*** (1.152)	1.639*** (0.624)
Thresholds			
Threshold 1 (non-user | infrequent user)	0.062 (0.19)	-4.308*** (1.029)	-4.732** (1.932)
Threshold 2 (infrequent user | frequent user)	0.357** (0.157)	1.694*** (0.475)	1.492 (0.921)

Model statistics:
Npar=31, LL_{EL}=-2653.15, LL_{MS}=-2406.42
LL_β=-2,112.36
$\rho^2_{EL,\ adj.}$=0.193, $\rho^2_{MS,adj.}$=0.109

Model statistics for equivalent univariate model:
Npar=31
LL_β=-2,117.01
$\rho^2_{EL,\ adj.}$=0.193, $\rho^2_{MS,adj.}$=0.107

***, **, * denote a statistical significance of less than 0.01, 0.05, 0.10, respectively.
[1] Defined based on the geocoded home addresses of the respondents and the classification presented by Salon (2015). This variable denotes a person living in urban or central city neighborhood types as defined in the Salon (2015) classification.
[2] Single item measured on a 5-level Likert type scale from strongly disagree to strongly agree.

4.6.2.2 Binary logit model of household vehicle deficiency

Table 24 presents the binary logit model of household vehicle deficiency. Income is negatively associated with living in a vehicle deficient household, although this effect is statistically insignificant for the "VA: Car Enthusiast & Dependent" cluster. The latter result may imply that even if a household has lower income, if attitudinal traits favor auto-oriented lifestyles, income does not appear to be a significant deterrent to owning as many vehicles as there are licensed drivers. This may be as much a matter of lifestyle-generated "necessity" as of preference, however; i.e. the need to own a higher number of automobiles could still impose something of a financial hardship. Furthermore, we see that the number of children in the household under 15 years old is statistically significant for the "VA: Non-car Dependent" cluster, indicating that a higher number of children decreases the likelihood of a household having an insufficient number of vehicles (possibly due to a higher demand for activities and personal travel).

A higher number of employed people in the household, moreover, is negatively associated with household vehicle deficiency status in the "VA: Car Enthusiast & Dependent" cluster, while this impact is practically and statistically insignificant in the "VA: Non-car Dependent Lower Income" cluster.

With respect to the impact of race, we see that White households in both clusters, when compared to the other races, are less likely to be among those with an insufficient number of vehicles (even after controlling for income, employment, and number of children), suggesting a racial inequality in vehicle availability among non-White households.

Finally, we see that built environment has a statistically significant relationship with vehicle deficient status in the "VA: Non-car Dependent Lower Income" cluster, where (even after controlling for income) households living in urban areas are more likely to be among those with fewer vehicles than licensed drivers. This result is as expected, since urban life tends to help promote less reliance on car ownership, given the higher density and better transit services in urban areas than in suburban or rural areas.

Table 24 Binary logit outcome model of belonging to a vehicle deficient household ($N_{\text{Training set}}$=2,412)

Explanatory variables	Vehicle deficient household clusters	
	Car Enthusiast & Dependent	Non-car Dependent Lower Income
	Coef.[1] (Robust S.E.)	Coef.[1] (Robust S.E.)
High income HH	-0.661 (6.713)	-0.253** (0.111)
No. children in the HH under 15 years old	0.998 (0.626)	-0.135*** (0.045)
No. of employed in the HH	-4.819*** (1.685)	0.069 (0.062)
White	-1.097** (0.554)	-0.215** (0.104)
Urban dweller[2]	-0.721 (0.778)	0.278*** (0.084)
Constant	-0.714 (0.477)	-0.067 (0.195)
Model statistics: *Npar=18* *LL_{EL}=-1,671.87, LL_{MS}=-1,138.87,* *LL_{β}=-1,040.36* *$\rho^2_{EL,adj.}$=0.367, $\rho^2_{MS,adj.}$=0.071*	*Model statistics for equivalent univariate model:* *Npar=17* *LL_{β}=-1,037.61* *$\rho^2_{EL,\ adj.}$=0.369, $\rho^2_{MS,adj.}$=0.074*	

***, **, * denote a statistical significance of less than 0.01, 0.05, 0.10, respectively.

[1]Since effect coding is used in the modeling process, the coefficient associated with the base level of the binary dependent variable (i.e., belonging to a vehicle-sufficient household) is no longer 0, but equal to the opposite sign of the reported coefficients here. For brevity, we have refrained from presenting those coefficients here.

[2] Defined based on the geocoded home addresses of the respondents and the classification presented by Salon (2015). This variable denotes a person living in urban or central city neighborhood types as defined in the Salon (2015) classification.

4.6.2.3 MNL model of expectations to change vehicle ownership

Table 25 shows the MNL model parameters of the expectations to change household's vehicle ownership (in the next three years). Consistent with the literature (as discussed in Section 4.3.3), the group of explanatory variables used in this model include the household's current level of vehicle ownership, its built environment, (expected) changes in life stage, and other variables including the impact of using carsharing services. With respect to the impact of the current number of household vehicles, we see that, in both clusters, a higher number is positively associated with an intention to decrease and negatively associated with an intention to increase (although this impact is statistically insignificant in the first cluster).

Furthermore, households in urban areas who belong to the "ECVO: Non-eco-friendly Car Enthusiast" cluster are more likely to express an intention to increase their VO levels, while this effect is reversed in the "ECVO: Eco-friendly Stable in Life" cluster (although it is statistically insignificant there). Considering that the "ECVO: Non-eco-friendly Car Enthusiast" cluster is comparatively less pro-urban than the other cluster, this result can possibly point to the higher intention of the urban dwellers in this cluster to move out and subsequently require a higher number of vehicles for personal travel.

In terms of expected changes in life stage, we see a statistically significant effect of finishing studies in the "ECVO: Eco-friendly Stable in Life" cluster, while interestingly this effect is statistically insignificant in the first cluster. Those who expect to graduate soon in the "ECVO: Eco-friendly Stable in Life" cluster are less likely to express an intention to decrease their household vehicle ownership and more likely to express an intention to increase.

With respect to the impact of using other shared mobility services, we generally see statistically weak effects. However, those in the "ECVO: Non-eco-friendly Car Enthusiast" cluster who are among the adopters of carsharing services are more likely to have an intention to decrease their vehicle ownership than their non-carsharing counterparts.

Table 25 MNL outcome model of expectations to change vehicle ownership (ECVO) ($N_{Training\ set}$=2,412)

Explanatory variables	Dependent variable level	ECVO cluster: Non-eco-friendly Car Enthusiast	ECVO cluster: Eco-friendly Stable in Life
		Coef.[1] (Robust S.E.)	Coef.[1] (Robust S.E.)
HH current no. of vehicles	Decrease	0.217 (0.912)	0.945*** (0.232)
	Undecided or keep the same	-0.054 (0.487)	0.270 (0.222)
	Increase	-0.164 (0.430)	-1.214*** (0.442)
Urban dweller[2]	Decrease	-1.641* (1.007)	0.419 (0.437)
	Undecided or keep the same	0.826* (0.52)	-0.005 (0.428)
	Increase	0.815* (0.511)	-0.414 (0.829)
End studies in the next 3 years	Decrease	0.700 (1.102)	-3.021*** (0.518)
	Undecided or keep the same	-0.720 (0.587)	-2.061*** (0.425)
	Increase	0.021 (0.56)	5.082*** (0.787)
Carsharing adopter	Decrease	3.125* (1.921)	-1.748 (2.657)
	Undecided or keep the same	-2.476 (2.01)	-0.479 (1.535)
	Increase	-0.650 (0.479)	2.226 (1.400)
Constant	Decrease	-3.114 (2.018)	-0.264 (0.390)
	Undecided or keep the same	1.734* (1.038)	4.072*** (0.337)
	Increase	1.381 (1.055)	-3.808*** (0.667)

Table 25 Cont'd

Model statistics:	*Model statistics for equivalent univariate model:*
Npar=25	*Npar=24*
LL_{EL}=-2,649.85, LL_{MS}=-1395.83, LL_{β}=-1247.25	LL_{β}=-1,277.24
$\rho^2_{EL,adj.}$=0.520, $\rho^2_{MS,adj.}$=0.089	$\rho^2_{EL,\ adj.}$=0.509, $\rho^2_{MS,adj.}$=0.067

***, **, * denote a statistical significance of less than 0.01, 0.05, 0.10, respectively.

[1] Effect coding has been used in the modeling process here.

[2] Defined based on the geocoded home addresses of the respondents and the classification presented by Salon (2015). This variable denotes a person living in urban or central city neighborhood types as defined in the Salon (2015) classification.

4.6.2.4 Prediction accuracy of the model

Although the JLC model provides improved interpretation of and a deeper insight into the relationship between our outcome variables and how the external variables affect them, it is also important to compare how it performs with respect to the prediction of the outcome variables. Table 26 presents a comparison of the prediction accuracy (defined as the share of correctly predicted cases, where the "predicted" alternative is the one with the highest predicted probability of being chosen) of the JLC model of this chapter with the equivalent univariate models (using prior class membership probabilities in both cases). As points of comparison, we trained and tested equivalent (same explanatory variables and number of classes) univariate latent class regression models for each outcome variable, in addition to traditional (ordinal, binary, and multinomial logit) models and their respective market share models.

Overall, we see very small improvements in the prediction accuracy of the outcome variables as a result of using the JLC framework. For ridehailing usage frequency, JLC performs similarly to its univariate counterpart. This improvement increases to 0.2 and 5.5 percentage points when using the univariate ordinal logit model and univariate market share model as the base, respectively.

With respect to the household vehicle deficiency status, we see that the JLC outperforms the univariate LC model by 0.6 percentage points, and further outperforms the univariate binary logit and market share models by 0.9 and 1.7 percentage points, respectively.

Regarding the expectations to change household's vehicle ownership, the JLC model performs similarly as the univariate LC and traditional models, while outperforming the market share model by 0.2 percentage points.

Table 26 Summary of the comparison of the prediction accuracy of the JLC model against univariate models on the test dataset (N_{Test}=695)

Outcome variable	Prediction accuracy[1]			
	Joint latent class model	Univariate latent class model	Univariate traditional model	Univariate market share model
Ridehailing usage frequency	0.601	0.601	0.599	0.546
Household vehicle deficiency status	0.851	0.845	0.842	0.834
Expectations to change household's vehicle ownership	0.764	0.764	0.764	0.762

JLC model's log-likelihood = -4,373.10
No. of parameters=74

[1] Prediction accuracy is defined as the number of correctly predicted cases divided by the total number of predicted cases.

4.7 Discussion

The results of the ridehailing frequency LC point to several interesting findings. Although literature often paints the younger generation as generally more pro-ridehailing and pro-urban while less pro-car, our analysis presents two (roughly equally-sized) clusters who are of similar average (younger) age, but showing distinctly different behavior and attitudes. The first RH cluster in our analysis, i.e. the “RH: Younger Eco-friendly” cluster, is predominantly ridehailing dependent, as a majority in it use ridehailing services on a regular basis, a characteristic in stark contrast with the “RH: Younger Non-eco-friendly” cluster, where only 2% are among the regular users. Therefore, in contrast with the results of some other studies such as Sikder (2019) and Tirachini and del Río (2019), we see a less straightforward relationship between age and ridehailing usage, a relationship where being younger is not necessarily associated with a higher ridehailing usage. On the other hand, we find a similar relationship between income and ridehailing usage frequency as compared to the literature: the membership model of our analysis points to the “RH: Younger Eco-friendlies” as having, on average, higher incomes than their counterparts, and the outcome model also consistently shows that being lower income diminishes the propensity for higher ridehailing usage across the three RH clusters.

With respect to the relationship between the ridehailing usage and household vehicle availability LC variables, our results draw a more detailed conclusion compared to the other studies discussed in Section 4.3.4. Our younger clusters who use ridehailing more frequently than the older cluster also contain a higher share of vehicle deficient households, a result further corroborated by the positive coefficients that associate the two younger clusters with the “VA: Non-car Dependent Lower Income” cluster. However, these two younger clusters with similar shares of vehicle deficiency show significantly different levels of ridehailing usage frequency, indicating that factors other than vehicle availability (such as built environment and attitudes) are associated with their difference in ridehailing usage.

Furthermore, the relationship between the vehicle availability and expectations to change VO LC variables shows a positive association between the “VA: Non-car Dependent Lower Income” and “ECVO: Non-eco-friendly Car Enthusiast” clusters, indicating that belonging to the “VA: Non-car Dependent Lower Income” cluster increases the likelihood of being associated with the “ECVO: Non-eco-friendly Car Enthusiast” cluster. Interpreting this relationship with respect to the distributions of their respective outcome variables shows that members of the VA cluster who are more likely to live in vehicle deficient households are also more likely to be among those in the ECVO cluster that has a higher share of those expressing an expectation of vehicle ownership increase in the future. This relationship, moreover, is more specifically corroborated in the ECVO outcome model where the MNL results show that a higher number of vehicles in the household is negatively associated with an increase intention, and positively associated with a decrease intention.

Finally, the relationship between the RH LC and the ECVO LC variables shows that the first two RH LC clusters (Younger Eco-friendly and Younger Non-eco-friendly) are both significantly and positively associated with the “ECVO: Non-eco-friendly Car Enthusiast” cluster, while the “RH: Older Car enthusiast” cluster is positively associated with the “ECVO: Eco-friendly Stable in Life” cluster. Comparing the coefficients associated with the two younger clusters, however, reveals that the “RH: Younger Non-eco-friendlies” are considerably more likely to belong to the “ECVO: Non-eco-friendly Car Enthusiast” cluster. In other words, although both clusters are of similar average age and contain approximately similar shares of vehicle deficient households, those in the cluster with a higher ridehailing usage are less likely to belong to the “ECVO: Non-eco-friendly Car Enthusiast” cluster. This result is also in line with the distribution of the expectations to change vehicle ownership within the RH LC, where a smaller share of those in the “RH: Younger Eco-friendly” cluster report a vehicle ownership increase intention than among the “RH: Younger Non-eco-friendlies”. This conclusion, therefore, hints at the future impact of ridehailing services, where its users, as they grow older and more stable in life, might be less likely to want to own more vehicles.

4.8 Summary and conclusion

In this chapter, we aimed to jointly study ridehailing usage frequency, household vehicle availability, and expectations to change household’s vehicle ownership while also accounting for unobserved heterogeneity in the data. To accomplish this goal, we proposed a joint (trivariate) latent class modeling framework that accounts for unobserved heterogeneity in the data through the probabilistically defined categorical latent variables (classes). One of the practical advantages of the proposed methodology is the flexibility to use any modeling framework of choice with any of the dependent variables, giving us the ability, in our context, to use ordinal logit, binary logit, and multinomial logit frameworks together to model the three dependent variables of this study. We further discussed how, as opposed to traditional trivariate models where the correlations among the error terms of the models provide little additional conceptual insight, this approach allows for the specification and meaningful interpretation of associations among the latent class variables.

Our results further confirm the impact of income and education on ridehailing usage frequency as reported in the literature, with those living in higher income households and having a higher education level tending to use these services more often. This study, however, provides more detailed insights with respect to the impact of age on ridehailing usage compared to the previous studies. Our RH LC model identifies two clusters of similar age and reported life-stability level, with one having a significantly higher ridehailing usage level. We further discussed the different characteristics that differentiate these clusters, and cautioned against homogeneously describing the younger generation as the more frequent users of ridehailing services.

We, moreover, discussed the relationship between ridehailing usage and vehicle availability, pointing out that, again, this relationship can be more nuanced than what is already discussed in the literature. Although the cluster with lower household vehicle availability tends to be positively associated with the two higher ridehailing usage clusters (although weakly in the Younger Eco-friendly case), we see substantially different ridehailing usage levels but similar shares of vehicle deficient households between the two RH clusters. This result, therefore, points out that the relationship between ridehailing usage and vehicle availability is not the same across all segments of the population.

With respect to the interaction of latent clusters associated with ridehailing usage and future intentions to change vehicle ownership levels, we concluded that, controlling for age (and life stability) and vehicle availability levels, those in the RH LC cluster with a higher usage of ridehailing services are less likely to belong to the Non-eco-friendly car enthusiast cluster than those in the cluster with a low usage of ridehailing. This result can further bolster the promise of a decreased car dependency in the future as a result of the availability of ridehailing services.

CHAPTER 5. CONCLUSIONS

5.1 Research summary

This dissertation aimed to investigate the role of two currently influential factors in the transportation domain, generational differences and shared mobility, in travelers' attitudes and choices. The results, laid out in three separate chapters, underlined the role of generational cohorts in attitudes while providing new evidence on the longevity of such effects. The results further provided new insights into the role of new mobility services in the travel behavior of individuals and how it varies by age and lifestyle cohorts.

As expounded upon in the first study of this dissertation, we found evidence of a generational divide in four transportation-related attitudes, although the magnitudes of the differences were fairly modest. The younger (Millennial) generation, consistent with expectations, exhibited attitudes that were more pro-urban living and pro-environment and less pro-car ownership compared to the older (Gen X) cohort. Although these differences shed further light on what makes the younger generation tick, they did not provide evidence on the sources of these differences and whether such generational differences will last over time as Millennials grow older and enter new life stages. To answer these questions, therefore, we linearly decomposed the generational gaps in the (average) linearly-regressed attitudes, and investigated what portion of these gaps can be attributed to life-stage variables (among the model's explanatory variables), hence identifying the portion of the gap that is more likely to change over time. For example, the role of life-stage disparities in the generational gap in the currently pro-urban attitude (all else equal) amounts to 24%

of the total gap, indicating that as Millennials' marriage rate, employment rate, and income rate matches those of the previous generation, we can expect them to become less currently pro-urban. With respect to the long-term pro-urban attitude, we see an outsized influence of the life-stage variables, with the overall influence of (the interaction of) marriage and number of children, income, and education amounting to 187% of the gap, indicating that the younger Millennials may turn even less long-term pro-urban than Gen Xers as they grow older (all else equal). Similarly, if the younger generation were married and had college degrees to the same extent as their older counterparts, the generational gap in the pro-car ownership attitude may diminish by 32%. Finally, we saw that with respect to the pro-environment attitudinal construct, it is unlikely that convergence of their life-stage variable shares to those of the Gen Xers will significantly impact this tendency – although convergence of the *coefficients* of those variables would. This study was among the first of its kind to apply the Blinder-Oaxaca decomposition method to the study of a travel behavior topic, and was specifically more unique with respect to studying generational attitudinal differences and their sources. The results not only help in obtaining a deeper understanding of the Millennials mindset, but also help in better placing into context their behavioral differences with the previous generation. Further research can build on the results of this analysis to obtain a more detailed picture of the Millennials' behavioral convergence with the previous generation, and how travel demand model assumptions should be modified for long-term planning.

In the second study, we investigated the heterogeneous modal impacts of ridehailing mobility among different sociodemographic groups. We identified three distinct latent clusters, with a clear age difference delineating them. In the younger cluster, ridehailing tends to have a negative impact on transit and taxi usage. In the clusters with older higher income ridehailers, by contrast, ridehailing usage seemed to be largely supplemental to the use of other modes, but when there *is* an impact, it tends to be a reduction in the usage of personal cars and taxi cabs. We, furthermore, investigated the relationship between the identified latent clusters and shared ridehailing usage in order to assess the sustainability promise of these services. We observed that shared ridehailing adoption rate and usage frequency are higher among the younger cluster where transit and taxis see sizable shares of usage decline as a result of using ridehailing services, and additionally 50% of the frequent shared ridehailers are associated with this cluster. We further discussed how these results cast doubt on the sustainability promise of shared mobility ridehailing services. This study, as discussed, was unique both in terms of its methodology (latent class model with distal outcome) which was among the first of its kind in the travel behavior domain, and also its application which studied *shared* ridehailing while connecting it to the overall modal impacts of ridehailing services. The results of this study can be of interest to both ridehailing companies who need to assess the urban mobility impact of their services, and also to transit and other public agencies who need a better understanding of how shared rides impact the usage of their services. The results of this study can also inform city planners and policy makers that promoting shared ride services does not always result in a more sustainable outcome.

Finally, and in the last study of this dissertation, we jointly investigated ridehailing usage and current decisions alongside future intentions regarding vehicle ownership and how they are subject to heterogeneity with respect to different lifestyles (age and attitudes). We found evidence of a more nuanced generational divide in ridehailing usage, where the younger generation is not necessarily a stronger consumer of ridehailing services. We highlighted how attitudes can help better delineate different clusters of users, and concluded that the subset of the younger generation defined by a lower pro-urban and pro-sustainable tendency has a drastically lower usage of ridehailing than their peers. Furthermore, although we saw a generally positive relationship between our lower vehicle availability cluster and higher ridehailing usage clusters, we found that this relationship is not the same across all segments of the population. In other words, the two younger ridehailing clusters who had substantially different ridehailing usage levels showed similar shares of vehicle deficient households, indicating that vehicle availability plays a different role in propelling the usage of ridehailing in different population segments. Finally, our results showed that controlling for age (and life stability) and vehicle availability levels, those in the ridehailing cluster with a higher usage of ridehailing services are less likely to belong to the latent cluster with a higher share of intentions to increase vehicle ownership than those in the cluster with a low usage of ridehailing, possibly bolstering the ridehailing promise of lower car ownership in the future. As discussed, this study was unique in terms of its proposed methodology which uses relationships among the different latent classes associated with outcome variables of different types to link those outcomes in a joint model, and to the best of our knowledge, is the first application of such models in the transportation field. The application of this method to timely topics in the travel behavior field also provides fresh insights that contribute to the growing knowledge on ridehailing, vehicle ownership, and their interaction. More specifically, the possible impact of ridehailing on future vehicle ownership rates can be of particular interest to both ridehailing companies and public agencies, helping design policies that incorporate ridehailing as one element of car ownership reduction.

5.2 COVID-19 and its impact on travel behavior

This dissertation, based on data predating the onset of the COVID-19 pandemic, does not address the temporary or long-term impacts of this pandemic on travel behavior. The ensuing lockdowns and social distancing policies meant to control the spread of the virus during this period, however, significantly changed the travel behavior of most people in the world. Average household trip rates fell significantly, along with congestion levels and car-induced air pollution. People largely shunned public or shared modes of travel such as mass transit and shared ridehailing, while active modes such as walking and bicycling saw an uptick in usage.

This unique situation provided cities with new challenges and opportunities. The rapidly declining transit usage, for example, made it increasingly difficult for transit agencies to continue to provide the same level of service, and portended a possibly stronger personal car use after the easing of lockdowns and work-from-home orders. Such a scenario not only draws a grim portrait of the escalating inequity in transportation, but also warns of even worse congestion and air pollution due to the increased car usage. On the other hand, cities gained a valuable opportunity to rethink their space allotments. With the increased demand for walking and biking, cities often found their sidewalks too narrow, broken, or in many cases non-existent, and city planners found renewed support for “taking back the cities from cars”. Indeed, how cities emerge after the pandemic could be a sign of the progressive thinking of their leaders.

With respect to shared mobility, a topic more closely investigated in this dissertation, we expect to see a disruption of the established trends. Not only have ridehailing trips decreased in number, but shared ridehailing services have been paused by the TNCs. Considering the results of this dissertation, a lower availability of drivers for ridehailing services in addition to people’s general aversion in sharing a car space during a pandemic might prompt an increase in vehicle ownership among those who relied more heavily on ridehailing as a means to move around. Exactly when we can expect these services to go back to normal is a product of how fast we can bring the pandemic under control, and how long the fear of the virus remains in the psyche of the public. Indeed, going back to normal and the progress made in promoting shared rides can take a few years, and then challenges will still remain. If TNCs, backed by their investors and business model, bounce back faster and stronger than the poorly funded transit agencies, we could see a stronger siphoning of users from transit to private or shared ridehailing services. Such a possible outcome, especially considering the findings of Chapter 3 where results already show a higher shared ridehailing usage, can likely come at the expense of transit, which forbodes a deepening sustainability and equity crisis. This possibility further underlines the urgent need for government support and funding of transit, and deliberate planning to help build back trust in using public and shared modes of transportation among the public.

5.3 Research limitations and directions for future research

The studies in this dissertation entail a number of limitations. All three studies are based on surveys of respondents in the state of California, which may make the generalizability of the results to the nation or other geographies difficult. One of the avenues for future research, therefore, is to replicate the current research methodology on survey data from other geographies, and investigate whether the identified patterns deviate from the California findings of this dissertation. With the current efforts on data collection at Georgia Tech and its collaborating institutes, especially, the prospects for more geographically-diverse data is ever more possible, and further assists the exploration of geographical transferability of this dissertation's findings.

More specifically, a limitation of the first study in this dissertation, where generational gaps in transportation-related attitudes were investigated, revolves around the cross-sectional design of the survey, which precludes deductions about whether the *coefficient* portion of the gap is likely to diminish over time. A useful extension of the current study would include using longitudinal data. A further useful extension (particularly in a new dataset with broader reach) would be to decompose differences between geographically distinct groups. Additionally, as a number of studies (e.g. Myers, 2016) indicate, the real-world impact of these attitudes and preferences would be determined by contextual factors, therefore future work that builds upon findings in this study will seek to investigate how much of the reduction in attitudinal gaps translates into behavioral choices. This intended extension would have direct policy implications, since policy-makers are often more interested in revealed behavioral choices.

In the second study of this dissertation, one initial limitation involved the use of the Uber API and geocoded home locations to identify those with access to shared rides, since we did not know whether respondents in our sample had access to shared ridehailing in their region. While we acknowledge that this approach is not perfect (people can use ridehailing services on trips or at the workplace), we believe it still provides a reasonable way to filter out those respondents who cannot use these services due to a lack of access. Another limitation regarding this study was the use of self-reported impacts of ridehailing services on other modes. Although self-reported claims might be less accurate than empirically observed changes, it still provides a reasonable estimate of the direction and strength of the modal impacts of ridehailing. A similar limitation also exists in the third study of this dissertation, where self-reported intentions of future changes in the vehicle ownership level of a household rather than actual revealed changes were used. Although expressed intentions may be less ideal than revealed changes, when longitudinal data are unavailable, expressed intentions can still be elucidating when it comes to the joint study of vehicle ownership and ridehailing usage.

An important extension to the study of Chapter 2 would be the application of the Blinder-Oaxaca decomposition method to *behavioral* differences between generations, and assessing what portion of such gaps are attributable to the differences in *attitudes* studied here. Considering the results of this study, therefore, we can provide a more accurate picture of how expected attitudinal changes contribute to possible behavioral changes of the younger generation as they grow older.

With respect to the methodology of Chapter 3 an interesting extension could be the use of LC tree models instead of traditional LC models to further explore population heterogeneity within each latent class, and then apply the distal outcome methodology to the LC tree model (Van Der Bergh and Vermunt, 2019). Latest developments in the psychometric field have made this application possible, but few studies have yet applied this methodology in different contexts. Moreover, an alternative approach to the three-step latent class model in our context is the joint estimation of an LC cluster model and LC regression through a joint distribution of their LC variables (similar to the study of Chapter 4). Further explorations are needed to evaluate the application of this method.

With regard to the methodology of Chapter 4, moreover, a useful extension of the work would be a direct comparison between a traditional trivariate model and the LC trivariate model used in this study in terms of interpretation and prediction power. It is also theoretically possible to use random parameters in the outcome models, further allowing for exploration of heterogeneity in the data. Furthermore, an exploration of the simultaneous estimation of the measurement models of the attitudes used in this study and the LC trivariate model can reduce measurement error in the modeling framework. Such an application, however, might cause problems in model estimation and convergence, and further imposes conditional independence assumptions that can be hard to control for, a topic that needs to be analyzed further in a future study. Finally, a limitation unique to the study of Chapter 4 was the implementation of the chain rule of conditional probability to jointly model the three LC variables, thereby imposing a conditional “directionality” on the membership model structure as opposed to a bidirectional correlation or non-recursive causal structure which could be more appropriate. A future direction of research, therefore, could be aiming to relax the directionality of the relationship among the LC variables and allow for a bidirectional correlation.

APPENDIX A. ATTITUDINAL REGRESSION MODELS AND AGGREGATED LIFE-STAGE DECOMPOSITIONS

A.1 Segmented regression model results

A.1.1 Currently pro-urban

Table A.1 summarizes segmented linear regression models for the pro-urban construct that primarily focuses on attitudes toward urban residential choice location in the present; i.e. *currently* pro-urban. We see that attributes related to childhood residential location, employment status, income, gender, race, political affiliation, education level of parents, and marital status are statistically significant predictors of the pro-suburban attitudinal construct for either the Millennials or the Generation X cohort (or both, as is the case for one variable).

Turning first to life-stage variables, we see that being married is associated with a lower pro-urban tendency, although this effect among Millennials is more attenuated in magnitude and significance relative to Gen Xers. Income level has a similar effect, with those who have annual incomes of $100,000 or more having less favorable attitudes toward urban living, relative to middle- and lower-income groups. Employment status, on the other hand, has an opposing effect, with Millennials who report themselves to be employed having higher tendencies to be pro-urban relative to those who are unemployed, a trend that is consistent but not significant for Gen Xers. Millennials who have a parent (or parents) with graduate-level education tend to be more pro-urban, while this influence is the opposite (though not significant) with Gen Xers, potentially pointing to a critical generational difference in how those raised in well-educated (higher-earning) households view the desirability of living in urban areas.

With regard to gender, female Millennials tend to be significantly less pro-urban than their male counterparts, a trend that is not present (or significant) for Gen Xers. We also see that childhood residential location appears to be influential, with those who report having been raised in the Northeastern United States tending to have more favorable attitudes toward urban living (relative to those raised elsewhere in the U.S.), while being raised in Hawaii has opposite effects between the Millennial and Gen X cohorts. With regard to race, Native Americans tend to be less pro-urban, while Asians tend to be more pro-urban, relative to other races. Lastly, political views have significant effects on attitudes toward urban living, with Democrats having a higher tendency to be pro-urban relative to those who identify as having Republican affiliations.

Table A.1 Segmented linear regression models for currently pro-urban attitude

Explanatory variables	Millennials		Generation X	
	Coefficient (Std. Err.)	p-value	Coefficient (Std. Err.)	p-value
Constant	0.178 (0.092)	0.054	0.084 (0.127)	0.509
Raised in Hawaii	1.570 (0.513)	0.002	-0.223 (0.244)	0.362
Raised in the Northeast	0.067 (0.320)	0.751	0.584 (0.221)	0.008
Native American	-0.400 (0.225)	0.076	-0.408 (0.159)	0.010
Asian	0.218 (0.098)	0.026	0.328 (0.107)	0.002

Table A.1 Cont'd

Female	-0.196 (0.082)	0.017	0.021 (0.092)	0.821
Married	-0.066 (0.085)	0.439	-0.336 (0.102)	0.001
High annual household income (> $100K)	-0.174 (0.094)	0.065	-0.134 (0.093)	0.148
Parent with graduate education	0.239 (0.106)	0.024	-0.136 (0.115)	0.239
Employed	0.164 (0.081)	0.043	0.088 (0.095)	0.356
Democratic affiliation	0.032 (0.092)	0.728	0.230 (0.097)	0.017
Republican affiliation	-0.477 (0.100)	<0.001	-0.140 (0.126)	0.267
Model statistics	N=1029 R^2=0.092		N=945 R^2=0.093	

A.1.2 Long-term pro-urban

Table A.2 summarizes the segmented regression models for the long-term pro-urban construct; as discussed in Section 2.6, this construct is segmented based on the younger Millennials cohort (< 26 years old) relative to an aggregate group of older Millennials and Generation X. We see that attributes related to childhood residential location, current residential location, race, income level, education level, political affiliation, and the interaction between marital status and children, are statistically significant predictors of the long-term pro-urban attitudinal construct. Notably, among younger Millennials, those who currently live in urban areas tend to have significantly more favorable attitudes toward long-term urban living than non-urban dwellers, an effect that is consistent but not significant for their older peers. With regard to childhood residential location, we see that among younger Millennials, those raised in the

Southeastern U.S. tend to have more favorable attitudes toward long-term urban living than others, an effect that is reversed in the older cohort (though the latter effect is at a lower level of significance than the former). On the other hand, among older Millennials and Gen Xers, those raised in Alaska tend to have stronger long-term urbanite attitudes than others, which is in line with those raised in Hawaii. In addition, those who identify as white in both cohorts being studied tend to have significantly more favorable attitudes toward long-term urban living relative to other races.

Turning now to life stage variables, we see that the interaction of being married and number of children (in the household) is significant for both cohorts, indicating that those who are married and with more children in the household tend to have less favorable attitudes toward long-term urban living. The constituent variables of the interaction term, though their coefficients are not statistically significant, are kept in the model to reduce bias in the estimates of the other coefficients, as is the general practice when including interaction terms in regression models (Braumoeller, 2004). Overall, these (constituent) terms indicate that those married with no children tend to have stronger long-term pro-urban tendencies, while those unmarried with more children in their household (possibly younger siblings, signifying Millennials who are still living at home), and therefore larger household sizes, have weaker long-term pro-urban tendencies. Additionally, we see that those with lower levels of education and income show a more favorable opinion toward living long-term in urban environments, although these variables are only significant for the younger Millennials cohort, who have a greater share of individuals still in college and therefore "artificially" have lower education and income levels. Finally, we see that

Republicans, in line with the currently pro-urban results, tend to have less positive attitudes toward long-term urban living, although this is only significant for the young Millennials cohort.

Table A.2 Segmented linear regression models for long-term pro-urban attitude

Explanatory variables	Young Millennials		Older Millennials & Generation X	
	Coefficient (Std. Err.)	p-value	Coefficient (Std. Err.)	p-value
Constant	-0.241 (0.085)	0.005	-0.215 (0.117)	0.067
Raised in the Southeast	-0.390 (0.157)	0.013	0.852 (0.566)	0.133
Raised in Hawaii	-0.018 (0.160)	0.912	0.893 (0.540)	0.090
Raised in Alaska	0.106 (0.376)	0.779	1.115 (0.214)	0.000
White	0.178 (0.069)	0.010	0.272 (0.118)	0.021
Number of children	0.028 (0.069)	0.685	0.050 (0.089)	0.570
Married*Number of children	-0.149 (0.079)	0.059	-0.406 (0.152)	0.008
Married	0.115 (0.092)	0.211	0.115 (0.202)	0.569
Low household income (<40K)	0.180 (0.069)	0.010	0.191 (0.113)	0.093
High school education only	0.239 (0.119)	0.046	0.143 (0.143)	0.318
Urban dweller	0.217 (0.09)	0.016	0.023 (0.149)	0.877
Republican affiliation	-0.206 (0.093)	0.027	-0.166 (0.124)	0.180
	N=430 R^2=0.106		N=1534 R^2=0.058	

A.1.3 Pro-car ownership

Table A.3 summarizes the segmented regression models for the pro-car ownership construct. We see that attributes related to childhood and current residential locations, gender, race, education level, marital status, occupation, student status, and political affiliation are all statistically significant predictors of pro-car ownership attitudes for either the Millennials cohort, the Generation X cohort, or for both cohorts – as is the case for three of these variables (significant at the 5% level). Urban dwellers tend to be less pro-car, although this effect is attenuated among Millennials, findings that parallel those of the pro-environment construct. As with the other attitudinal constructs studied, childhood residential location is a significant predictor of attitudes toward car ownership, with those raised in the Southeast having a greater desire to own a car, although this is only significant for the Generation X cohort. Moreover, Millennials raised in Hawaii tend to be less pro-car. Interestingly, if we consider the results from the currently pro-urban model, we see that Millennials raised in Hawaii also tend to be more pro-urban.

Regarding race, Whites and African-Americans tend to have more favorable views toward car ownership, while Asians have less favorable views, relative to the base group which represents all other races (Native Americans, mixed race, and others). Gender is also a significant predictor, with women tending to have more favorable car ownership attitudes than men. This could be related to safety and privacy concerns that are more prevalent among women; for example, the literature reports that women are more likely to feel unsafe while waiting for transit (Fan, Guthrie, & Levinson, 2016). With respect to education, those with a high school education, and those who are college students, are less insistent on owning a car, potentially because of lower income levels and overall needs relative to those with higher education levels. Those who identify as Republican tend to have more favorable views toward owning a car, and in conjunction with previously reported results, we see that Republicans in the sample tend to be less pro-urban, less pro-environment, and more pro-car ownership than those of other political affiliations. Further, those who are employed in service industries tend to have more favorable views toward car ownership, potentially due to the demands of their jobs (ex. plumber/repairmen who depend on their vehicles to move between jobs).

Table A.3 Segmented linear regression models for pro-car ownership attitude

Explanatory variables	Millennials		Generation X	
	Coefficient (Std. Err.)	p-value	Coefficient (Std. Err.)	p-value
Constant	-0.182 (0.111)	0.102	-0.34 (0.127)	0.008
Raised in Hawaii	-0.976 (0.281)	0.001	0.352 (0.337)	0.296
Raised in Southeast	0.459 (0.169)	0.007	0.063 (0.151)	0.679
Native American	0.571 (0.129)	0.000	0.423 (0.178)	0.018
White	0.022 (0.088)	0.806	0.343 (0.112)	0.002
African-American	0.363 (0.160)	0.024	0.578 (0.190)	0.002
Asian	-0.336 (0.107)	0.002	-0.044 (0.138)	0.749
Female	0.236 (0.078)	0.003	0.025 (0.088)	0.776
High school education only	-0.277 (0.099)	0.005	-0.173 (0.133)	0.194
Student	0.005 (0.085)	0.955	-0.388 (0.113)	0.001
Urban dweller	-0.216 (0.081)	0.008	-0.312 (0.164)	0.056
Married	-0.059 (0.085)	0.493	0.272 (0.093)	0.003
Republican affiliation	0.334 (0.115)	0.004	0.447 (0.117)	0.000

Table A.3 Cont'd

Employed in service industry	0.079 (0.173)	0.646	0.399 (0.137)	0.004
	N=1029 R^2=0.110		N=945 R^2=0.138	

A.1.4 Pro-environment

Table A.4 summarizes the segmented regression models for the pro-environment attitude. We see that attributes related to childhood residential location, current residential location, race, income level, education level, employment status, student status, and political affiliation are all statistically significant predictors of attitudes toward environmentally-conscious living for either the Millennials cohort, the Generation X cohort, or for both cohorts – as is the case for five of these variables (significant at the 5% level). With regard to current residential location, living in an urban area tends to indicate more favorable pro-environment attitudes for both cohorts – as was also the case for the long-term urban living attitudinal construct. This result is supported by the positive correlations between the pro-urban and pro-environment attitudinal constructs discussed in Section 2.5. Turning now to childhood residential location, we see that (all else equal) Millennials and Gen Xers raised in Alaska appear to be less pro-environment relative to those raised in other regions. However (perhaps surprisingly), Millennials raised in the Pacific region of the U.S. also have significantly lower pro-environmental attitudes relative to those raised in other regions (besides Alaska), a trend that is not reflected for Gen Xers.

Being a member of either Hispanic or Asian racial/ethnic groups is a significant predictor of environmental attitudes for both cohorts, with members of these groups tending to be more pro-environment than those from other races (Whites, African-

Americans, Native-Americans, Mixed-races, and others). Furthermore, among Millennials, those who are students, employed, or have high individual income levels (> \$100K) tend to be more pro-environment than their counterparts, while for the same groups of Gen Xers, although the average effects are also positive, they are smaller and not statistically significant. This observation suggests a generational divide in which employed Millennials with or without well-paying jobs demonstrate a greater care toward the environment than the preceding generation. Lastly, political affiliation appears to be closely associated with the pro-environment attitude, with those identifying as Republican in both generations demonstrating substantially lower inclinations toward environmentally-conscious living, while their Democratic counterparts tend to score higher on this attitude.

Table A.4 Segmented linear regression models for pro-environment attitude

Explanatory variables	Millennials		Generation X	
	Coefficient (St. Err.)	p-value	Coefficient (St. Err.)	p-value
Constant	-0.339 (0.086)	<0.001	-0.292 (0.100)	0.004
Raised in the Pacific region	-0.329 (0.159)	0.039	0.202 (0.221)	0.361
Raised in Alaska	-0.495 (0.197)	0.012	-1.193 (0.401)	0.003
Asian	0.148 (0.086)	0.087	0.453 (0.094)	<0.001
Hispanic	0.203 (0.082)	0.013	0.275 (0.114)	0.017
Urban dweller	0.186 (0.088)	0.034	0.299 (0.124)	0.016
Student	0.347 (0.079)	<0.001	0.190 (0.190)	0.318
Employed	0.310 (0.077)	<0.001	0.055 (0.086)	0.519

Table A.4 Cont'd

High individual income (> $100K)	0.497 (0.194)	0.011	0.062 (0.143)	0.667
Republican affiliation	-0.499 (0.112)	<0.001	-0.419 (0.150)	0.005
Democratic affiliation	0.157 (0.081)	0.052	0.262 (0.094)	0.005
Model statistics	N=1029 R^2=0.143		N=945 R^2=0.127	

A.2 Aggregated contributions of life-stage variables to the attitudinal gaps

To facilitate a better understanding of the role of life-stage variables in the attitudinal gaps, Tables A.5-A.8 provide the decomposition results aggregated by variable type. Such aggregated decompositions provide additional insight into the size and direction of the contribution of each term related to each group of variables. For example, we see that, with the exception of the long-term pro-urban attitude (Table A.6), the coefficient effects of the life-stage variables (specifically employment status, income, education level, marital status, and interaction of marital status and number of children) tend to dwarf the corresponding endowment effects.

As mentioned, although we can somewhat confidently discuss the effect of changes in *endowments* on the gaps, our understanding of how model *coefficients* may change over time as a generation grows older, and the effects of those changes on the generational gaps, is much more indistinct and requires additional study. Our results, nonetheless, imply that changes stemming from life-stage model coefficients can impact the existing attitudinal gaps to a greater extent than changes in the endowments, and, accordingly, that the younger generation's uniqueness may be traced back more to these coefficient disparities than to their current life-stage share disparities.

Table A.5 Decomposition of the gap in currently pro-urban attitude, aggregated by variable type

	Endowment	Coefficient	Interaction	Total
Life-stage	-0.039	-0.144	-0.075	-0.258
Other variables	-0.013	0.190	0.013	0.190
Constant term	-	-0.093	-	-0.093
Total	-0.052	-0.048	-0.061	-0.161

Table A.6 Decomposition of the gap in long-term pro-urban attitude, aggregated by variable type

	Endowment	Coefficient	Interaction	Total
Life-stage	-0.270	0.042	0.156	-0.072
Other variables	0.005	-0.035	-0.021	-0.051
Constant term	-	-0.026	-	-0.026
Total	-0.265	-0.019	0.135	-0.149

Table A.7 Decomposition of the gap in pro-car ownership attitude, aggregated by variable type

	Endowment	Coefficient	Interaction	Total
Life-stage	0.062	0.107	0.106	0.275
Other variables	0.020	0.020	0.038	0.078
Constant term	-	-0.158	-	-0.158
Total	0.082	-0.032	0.145	0.195

Table A.8 Decomposition of the gap in pro-environment attitude, aggregated by variable type

	Endowment	Coefficient	Interaction	Total
Life-stage	0.009	-0.275	-0.042	-0.308
Other variables	-0.055	0.175	-0.008	0.112
Constant term	-	0.047	-	0.047
Total	-0.047	-0.052	-0.050	-0.149

APPENDIX B. MODAL IMPACTS OF RIDEHAILING'S LC MODEL PARAMETERS

Table B.1 LC cluster model parameters and descriptive statistics

Model variables	Descriptive statistics per class			Membership model parameters		
	Variable means/share per cluster			Class 1: Subst.	Class 2: Car augm.	Class 3: MM aug.
	Class 1: Subst. (22.5%)	Class 2: Car augm. (56%)	Class 3: MM aug. (21.5%)	Coef. (S.E.)	Coef. (S.E.)	Coef. (S.E.)
Model Indicators						
Personal car use						
Less	0.34	0.19	0.17	-0.220 (0.174)	-0.059 (0.178)	0.279 (0.247)
Same	0.45	0.70	0.81	-0.725 (0.159)	0.008 (0.16)	0.718 (0.226)
More	0.05	0.03	0.01	0.061 (0.352)	0.776 (0.341)	-0.836 (0.495)
Not a user	0.16	0.08	0.02	0.885 (0.268)	-0.725 (0.297)	-0.160 (0.455)
Bicycle use						
Less	0.32	0.02	0.02	1.111 (0.262)	-0.488 (0.302)	-0.623 (0.431)
Same	0.36	0.22	0.93	-0.882 (0.174)	-0.247 (0.195)	1.129 (0.246)
More	0.07	0.00	0.03	0.303 (0.349)	-1.254 (0.425)	0.951 (0.41)
Not a user	0.25	0.76	0.03	-0.532 (0.274)	1.989 (0.262)	-1.457 (0.444)
Bus use						
Less	0.62	0.06	0.04	0.394 (1.149)	0.306 (1.949)	-0.700 (1.517)
Same	0.21	0.15	0.94	-1.328 (1.151)	0.081 (1.959)	1.247 (1.531)
More	0.11	0.00	0.00	2.817 (3.411)	-2.880 (5.846)	0.063 (4.54)
Not a user	0.06	0.78	0.02	-1.883 (1.203)	2.493 (1.97)	-0.610 (1.597)
Light rail use						
Less	0.46	0.05	0.02	-0.352 (0.953)	-0.481 (0.961)	0.833 (1.831)

Table B.1 Cont'd

Same	0.23	0.21	0.93	-1.480 (0.981)	-0.079 (0.923)	1.558 (1.817)
more	0.09	0.01	0.00	2.450 (2.737)	1.219 (2.705)	-3.669 (5.367)
Not a user	0.22	0.72	0.04	-0.619 (0.940)	-0.660 (0.927)	1.278 (1.813)
Commuter rail use						
Less	0.39	0.01	0.00	1.764 (0.759)	-0.280 (0.773)	-1.485 (1.447)
Same	0.27	0.11	0.93	-0.568 (0.433)	-0.503 (0.326)	1.071 (0.666)
More	0.04	0.01	0.01	-0.875 (0.754)	-0.570 (0.494)	1.444 (0.993)
Not a user	0.31	0.87	0.05	-0.322 (0.389)	1.352 (0.33)	-1.031 (0.621)
Taxi use						
Less	0.60	0.32	0.36	-0.329 (1.313)	-0.611 (1.31)	0.940 (2.61)
Same	0.13	0.11	0.59	-0.991 (1.318)	-0.952 (1.313)	1.943 (2.610)
More	0.04	0.01	0.00	1.725 (3.922)	1.118 (3.923)	-2.843 (7.819)
Not a user	0.23	0.56	0.05	-0.406 (1.317)	0.445 (1.314)	-0.039 (2.615)
Inactive Covariates						
Age (years, continuous)	40.75	47.79	45.66	–	–	–
Income (categorical)						
< $50K/yr	0.28	0.17	0.15	–	–	–
>$50K/yr, <$100K/yr	0.33	0.30	0.32	–	–	–
> $100K/yr	0.38	0.53	0.53	–	–	–
Car ownership (binary)						
Do not own a car	0.25	0.07	0.06	–	–	–
Education (binary)						
Bachelor's degree or higher	0.59	0.72	0.78	–	–	–
Built environment (binary)						

Table B.1 Cont'd

Urban dwellers	0.55	0.36	0.41	–	–	–
Attitudes (factor score, continuous)						
Car enthusiast	-0.57	0.03	-0.29	–	–	–
Pro suburban	-0.29	-0.06	-0.24	–	–	–
Pro sustainability	0.57	0.16	0.45	–	–	–

APPENDIX C. JLC MEMBERSHIP MODEL PARAMETERS OF CHAPTER 4

Table C.1 JLC membership model parameters

Dependent variable (level)	Explanatory variable (level)	Coef.	Robust S.E.	Z-value	p-value
		RH LC membership model			
RHClass(1)	Constant	1.475^{***}	0.404	3.649	<0.001
RHClass(2)	Constant	1.277^{***}	0.442	2.891	0.004
RHClass(3)	Constant	-2.752^{***}	0.755	-3.642	<0.001
RHClass(1)	Age	-0.030^{***}	0.007	-4.249	<0.001
RHClass(2)	Age	-0.029^{***}	0.006	-4.655	<0.001
RHClass(3)	Age	0.059^{***}	0.010	5.777	<0.001
RHClass(1)	FS Pro-sustainable	0.286^{***}	0.049	5.796	<0.001
RHClass(2)	FS Pro-sustainable	-0.203^{**}	0.103	-1.975	0.048
RHClass(3)	FS Pro-sustainable	-0.083	0.092	-0.896	0.370
RHClass(1)	FS Eco-minimalist	0.105^{**}	0.050	2.094	0.036
RHClass(2)	FS Eco-minimalist	-0.191^{**}	0.079	-2.420	0.016
RHClass(3)	FS Eco-minimalist	0.086	0.083	1.032	0.300
RHClass(1)	FS Pro-urban	0.150^{**}	0.059	2.552	0.011
RHClass(2)	FS Pro-urban	-0.319^{***}	0.090	-3.556	<0.001
RHClass(3)	FS Pro-urban	0.169^{**}	0.086	1.964	0.049
		VA LC membership model			
VAClass(1)	Constant	0.160	0.138	1.161	0.250
VAClass(2)	Constant	-0.160	0.138	-1.161	0.250
VAClass(1)	RHClass(1)	-0.001	0.106	-0.008	0.990
VAClass(2)	RHClass(1)	0.001	0.106	0.008	0.990
VAClass(1)	RHClass(2)	-0.357^{*}	0.214	-1.667	0.096
VAClass(2)	RHClass(2)	0.357^{*}	0.214	1.667	0.096
VAClass(1)	RHClass(3)	0.358^{**}	0.171	2.090	0.037
VAClass(2)	RHClass(3)	-0.358^{**}	0.171	-2.090	0.037
VAClass(1)	FS Car enthusiast	0.348^{***}	0.094	3.691	<0.001
VAClass(2)	FS Car enthusiast	-0.348^{***}	0.094	-3.691	<0.001
VAClass(1)	FS Busy car dependent	0.191^{***}	0.073	2.599	0.009
VAClass(2)	FS Busy car dependent	-0.191^{***}	0.073	-2.599	0.009
VAClass(1)	FS Pro-urban	-0.171^{**}	0.076	-2.264	0.024
VAClass(2)	FS Pro-urban	0.171^{**}	0.076	2.264	0.024
		ECVO LC membership model			

Table C.1 Cont'd

ECVOClass(1)	Constant	-0.940**	0.410	-2.293	0.022
ECVOClass(2)	Constant	0.940**	0.410	2.293	0.022
ECVOClass(1)	RHClass(1)	0.499**	0.248	2.011	0.044
ECVOClass(2)	RHClass(1)	-0.499**	0.248	-2.011	0.044
ECVOClass(1)	RHClass(2)	1.431***	0.382	3.750	<0.001
ECVOClass(2)	RHClass(2)	-1.431***	0.382	-3.750	<0.001
ECVOClass(1)	RHClass(3)	-1.930***	0.501	-3.851	<0.001
ECVOClass(2)	RHClass(3)	1.930***	0.501	3.851	<0.001
ECVOClass(1)	VAClass(1)	-0.710**	0.302	-2.352	0.019
ECVOClass(2)	VAClass(1)	0.710**	0.302	2.352	0.019
ECVOClass(1)	VAClass(2)	0.710**	0.302	2.352	0.019
ECVOClass(2)	VAClass(2)	-0.710**	0.302	-2.352	0.019
ECVOClass(1)	FS Car enthusiast	0.460**	0.233	1.973	0.048
ECVOClass(2)	FS Car enthusiast	-0.460**	0.233	-1.973	0.048

***, **, * denote a statistical significance of less than 0.01, 0.05, 0.10, respectively.

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